

Essays on Dynamic Macroeconomics and Risk Attitudes

by

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To my family

Biographical note

I was born in 1981, in the city of Porto, Portugal, where I later completed my undergraduate education in Economics at the School of Economics and Management of the University of Porto. I began my professional career in 2006, working as a Research Assistant for Professor Nuno Sousa Pereira at the Research Centre in Industrial, Labour and Managerial Economics (CETE). I have also worked as an Economist at the Portuguese Ministry of Finance and at the Portuguese Healthcare Regulation Authority, and since 2009 I collaborate as a Researcher on the South African Panel Study of Small Business and Health, a research project coordinated by Professor Li-Wei Chao. I currently work as an Economist at the Portuguese Public Finance Council.

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Abstract

This thesis is a collection of three essays in Economics. The first essay concerns the difference in the business cycle volatility of the unemployment rates of high-skill and low-skill workers. I show that from the late 1990s onwards the business cycle volatility of the unemployment rate has been higher for high-skill workers in the United States and thirteen European Union countries. I address this volatility gap with a business cycle model in which firms value skill diversity, each worker supplies a specific variety of skill, and households pay a cost to search and find new jobs. I calibrate the model to United States data and show it can successfully replicate the observed unemployment volatility gap, as well as generate unemployment rates that are substantially more volatile than output.

The second paper modifies a standard two-country international business cycle model to allow for a state-dependent risk aversion parameter, and investigates whether key mismatches between the theory and the data can be explained by varying risk aversion. I show that even though the dynamics of the exchange rate are linked with the behavior of the risk aversion parameter, under a reasonable calibration the volatility of the exchange rate is largely unaffected by how strongly countercyclical risk aversion is. In contrast, I find that the correlation between the movements in the exchange rate and the movements in the consumption ratio is substantially reduced in the presence of countercyclical risk aversion. I show that these results hold under different assumptions about the behavior of the risk aversion parameter, and under different assumptions about the household's preferences over the consumption-leisure bundle.

The third essay investigates the relationship between risk taking propensity and economic and health expectations using data from a longitudinal survey conducted in the Tshwane Municipality, South Africa. I find evidence that economic expectations significantly predict risk taking propensity, with better expectations being associated with higher willingness to take risks. The results hold with two different measurement scales for risk attitudes, and hold under a variety of robustness checks. I find some evidence that health expectations predict risk taking propensity, but the robustness checks fail to confirm the results. The findings highlight a channel through which economic expectations can affect decision making under risk, and I discuss its potential implications for entrepreneurial activity and our understanding of asset bubbles.

Resumo

A presente tese reúne três ensaios na área científica da Economia. O primeiro ensaio relaciona-se com a temática da volatilidade das taxas de desemprego dos trabalhadores qualificados e não qualificados. Apresenta-se evidência empírica de que, a partir do final dos anos 90, a volatilidade da taxa de desemprego nos Estados Unidos e em treze países europeus é superior para os trabalhadores qualificados. Este diferencial de volatilidade é analisado no âmbito de um modelo de ciclos de negócios reais em que as empresas valorizam a diversidade de qualificações, cada trabalhador oferece uma qualificação única e as famílias suportam os custos de procura de novos empregos. Uma calibração do modelo para os Estados Unidos replica o diferencial de volatilidade observado nos dados, bem como a maior volatilidade da taxa de desemprego face ao produto.

O segundo ensaio apresenta uma extensão do modelo de ciclos de negócios internacionais com duas economias, a qual contempla famílias com aversão ao risco variável, investigando-se o efeito desta modificação sobre discrepâncias existentes entre o modelo e os dados. Os resultados demonstram que embora a dinâmica da taxa de câmbio esteja relacionada com a aversão ao risco, uma calibração plausível deste modelo não modifica substancialmente a volatilidade da taxa de câmbio face ao modelo padrão, mantendo-se esta substancialmente abaixo do que é observado nos dados. Em contraste, os resultados demonstram que a correlação entre os movimentos da taxa de câmbio e os movimentos do rácio do consumo é menor na presença de aversão ao risco contra-cíclica, reduzindo substancialmente o diferencial entre o modelo e os dados. A análise de robustez mostra que estes resultados se verificam com diferentes especificações para as preferências das famílias e para o comportamento do parâmetro de aversão ao risco.

O terceiro ensaio investiga a relação entre a aversão ao risco e as expectativas que os indivíduos formam sobre a economia e sobre o seu próprio estado de saúde, usando para o efeito dados longitudinais provenientes de um inquérito realizado no município de Tshwane, na África do Sul. Apresenta-se evidência de que as expectativas económicas constituem um previsor estatisticamente significativo da aversão ao risco, estando melhores expectativas associadas a uma menor aversão ao risco. Estes resultados verificam-se em duas escalas usadas para medir a aversão ao risco e são confirmados por uma variedade de testes de robustez. A evidência sugere que as expectativas sobre o próprio estado de saúde podem constituir um previsor da aversão ao risco, mas este resultado não é confirmado sob diferentes testes de robustez. Este ensaio realça um canal através do qual as expectativas económicas podem influenciar a tomada de decisão em contexto de risco, discutindo-se também as suas potenciais implicações para a actividade empreendedora e para a formação de bolhas especulativas.

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Chapter 1

Introduction

This thesis is a collection of essays on three different topics in Economics: unemployment, open economy macroeconomics, and risk attitudes. In the first essay, titled “*Differences in the cyclical behavior of high-skill and low-skill unemployment*”, I examine differences in the business cycle volatility of the unemployment rates of high-skill and low-skill workers. I begin by presenting evidence that from the late 1990s onwards the unemployment rate has been more volatile for high-skill workers than for low-skill workers in the United States and thirteen E.U. countries. For the United States, I present additional evidence suggesting that before the mid-1980s the business cycle volatility of the unemployment rates was instead higher for low-skill workers. I then introduce a new framework to model unemployment into a business cycle model with worker heterogeneity, and I use this setup to address the unemployment volatility differences observed in the data.

In the model, households are composed by a continuum of high-skill and low-skill workers who offer specific skill varieties in the labor market, and the household derives monopolistic profits from each skill variety that is employed. In contrast with the traditional search and matching model of Mortensen and Pissarides (1994), households bear the costs of searching and finding new jobs, and in equilibrium they balance those costs with the gains associated with expanding the number of skill varieties that are employed. On the production side, the model features firms that exhibit a “taste for variety” in their labor inputs: the productivity of labor increases when a larger set of skill varieties is used. The intuition is that as the number of workers with differentiated skills increases, so does the scope for specialization gains.

A calibration of this model replicates two key features of the post mid-1980s U.S. data: (i) the simulations yield unemployment rates that are more volatile for high-skill

workers than for low-skill workers; and (ii) the simulations yield unemployment rates that are substantially more volatile than output. However, the model cannot easily account for the patterns of volatility in the U.S. unemployment rates prior to the mid-1980s: after accounting for differences in other features of the labor market such as the relative supply of high-skill workers and the average unemployment rates, the model still yields higher volatility for the unemployment rate of high-skill workers, in contrast with the data. I show that while the fit between the model and the data can be improved by a calibration in which the parameter that governs the “taste for variety” varies across periods, the mismatch relative to the period before the mid-1980s persists.

In the second essay, titled “*Countercyclical risk aversion in a two-country international business cycle model*”, I develop an extension of the standard two-country business cycle model (Backus et al., 1994) in which risk aversion is allowed to fluctuate in response to economic conditions, and I examine whether this modification changes key mismatches that exist between the theory and the data. In the model, I use recursive preferences (Kreps and Porteus, 1978; Epstein and Zin, 1989) to disentangle risk aversion from the elasticity of intertemporal substitution, which is kept fixed, and assume that risk attitudes shift in response to output fluctuations. In line with evidence from the literature (e.g., Beber and Brandt, 2006; Guiso et al., 2013; Hoffmann et al., 2013; Cohn et al., 2015) I assume that during periods of economic expansion risk aversion decreases below its baseline level, and during periods of economic contraction risk aversion increases above its baseline level.

In the standard two-country model, the exchange rate and the Home-Foreign consumption ratio are perfectly correlated, but in the data the correlation is typically close to zero or negative. This mismatch, known as the Backus and Smith (1993) puzzle, is substantially reduced in the model with countercyclical risk aversion, as the simulated correlation between the exchange rate and the consumption rate is close to 0.5. On the other hand, introducing countercyclical risk aversion in the model has no substantial effect on another mismatch known as the “quantity anomaly” (Backus et al., 1995). In the standard two-country model the simulated cross-country correlation of consumption is larger than the cross-country correlation of output, whereas in the data the correlations are stronger for output than for consumption. The extension presented here exhibits the same mismatch, with the cross-country correlation of consumption being about five times larger than the cross-country correlation of output.

I show that these results hold under different specifications for the law of motion of

risk aversion that include either a richer lag structure, or an asymmetric response of risk aversion to economic expansions and economic contractions. I also analyze how the results fare beyond the Cobb-Douglas utility kernel used in the standard two-country model, and find that using a GHH utility kernel (Greenwood et al., 1988) yields some improvement to the results.

In the third essay, titled “*Expectations and risk attitudes: Evidence from a longitudinal survey in Tshwane, South Africa*”, I use longitudinal data from a large-scale survey conducted in the Tshwane Municipality, South Africa, to examine how risk attitudes relate to economic and health expectations. Economists and psychologists have devoted a substantial amount of research to understanding the determinants of risk aversion, examining the effects of sociodemographic characteristics (e.g., Dohmen et al., 2011), genetic factors (e.g., Cesarini et al., 2009; Kuhnen and Chiao, 2009), exposure to natural disasters (e.g., Eckel et al., 2009; Page et al., 2014; Cameron and Shah, 2015) or economic shocks (see, e.g., Malmendier and Nagel, 2011), but the effects associated with expectations remain relatively unexplored.

I investigate how risk attitudes respond to two types of expectations relevant to the respondents of the survey: (i) economic expectations, which are relevant because people in the sample face a paucity of wage work and often resort to running small businesses to earn an income; and (ii) expectations that respondents have about their own health, which are relevant because people in the sample face a large variance in disease prevalence, including HIV, with varying current and future consequences. On fixed-effects regressions that control for a set of sociodemographic characteristics, I find that both types of expectations significantly predict the willingness to take risks, with better expectations being associated with a higher willingness to take risks. In a series of robustness checks that look into issues related to the measurement of risk attitudes, survey attrition, and autocorrelated disturbances I find that the results regarding economic expectations hold, but the results regarding health expectations do not.

The results presented in this essay provide three contributions to the literature. First, they expand the body of evidence related to the determinants of risk attitudes, not only with respect to the effects of expectations, but also with respect to the effects of sociodemographic characteristics, replicating previous findings related to age, marital status and life satisfaction. Second, the results about expectations feed into the debate about the stability of risk attitudes over time, contributing evidence that is compatible with recent studies which suggest that risk preferences may have a time-varying component (Guiso and Paiella, 2008; Malmendier and Nagel, 2011;

Cohn et al., 2015). Finally, the results are also relevant for policymakers because they highlight how decision making under risk may be affected by policies that shift people's expectations.

Chapter 2

Differences in the cyclical behavior of high-skill and low-skill unemployment

2.1 Introduction

Labor market outcomes for high-skill workers and low-skill workers differ greatly. On average, high-skill workers earn higher wages and face lower unemployment rates than low-skill workers do. A substantial amount of research in economics has been devoted to the study of the aforementioned wage difference, and there is now an extensive literature that examines the behavior of the skill premium (see, e.g., Katz and Murphy, 1992; Acemoglu, 2003; Lindquist, 2004; Autor et al., 2008; Heathcote et al., 2010). Similarly, differences between the unemployment rates of high-skill and low-skill workers have motivated a vast literature in economics. Some studies present evidence of how unemployment is less prevalent among high-skill workers than among low-skill workers (see, e.g., Mincer, 1991; Topel, 1993; Manacorda and Petrongolo, 1999), and other studies show that the gap between the unemployment rates of the two groups has widened over time (see, e.g., Murphy and Topel, 1987; Nickell and Bell, 1996). But along the business cycle the labor market outcomes for high-skill and low-skill workers are also different in terms of the volatility of their unemployment.

In Table 2.1 we present evidence of a volatility gap in the cyclical component of the unemployment rates of high-skill and low-skill workers in the United States

TABLE 2.1: CYCLICAL VOLATILITY OF THE UNEMPLOYMENT RATE IN THE UNITED STATES AND THIRTEEN E.U. COUNTRIES, BY SKILL GROUP

Country	Period	Low-skill workers	High-skill workers	Ratio high-low
Austria	1999:Q1–2016:Q4	8.45	17.39	2.06
Belgium	1999:Q1–2016:Q4	7.73	10.53	1.36
Bulgaria	2000:Q1–2016:Q4	13.51	17.46	1.29
Czech Republic	1998:Q1–2016:Q4	12.18	14.03	1.15
Finland	2000:Q1– 2016:Q4	7.34	8.45	1.15
France	2003:Q1– 2016:Q4	5.06	6.91	1.36
Germany	2005:Q1– 2016:Q4	4.26	6.40	1.50
Hungary	1999:Q1– 2016:Q4	6.59	10.72	1.63
Ireland	2000:Q1–2016:Q4	13.27	14.79	1.11
Italy	2001:Q1–2016:Q4	6.43	8.37	1.30
Luxembourg	2003:Q1–2016:Q4	13.88	20.39	1.47
Portugal	1998:Q1–2016:Q4	9.74	12.92	1.33
United Kingdom	2000:Q1–2016:Q4	6.74	8.61	1.28
United States	1998:Q1–2016:Q4	13.11	15.84	1.21

Notes: The statistics reported are standard deviations (in percent). Data are log-transformed quarterly unemployment rates, presented as deviations from a Hodrick-Prescott filtered trend with the smoothing parameter set to 1600. Data for the United States are obtained from monthly series of the *Current Population Survey*, and data for the E.U. countries are from the *European Union Labor Force Survey*. See the text for additional details.

and thirteen European Union countries. The data are seasonally adjusted quarterly log unemployment rates, presented as deviations from an Hodrick-Prescott filtered trend with the smoothing parameter set to 1600.¹ For the United States the data are computed from monthly series of the *Current Population Survey*, and for the E.U. countries the data are from the *European Union Labor Force Survey*. In all countries the data refers to individuals aged between 20 and 64 years old, which we categorize as high-skill workers if the data indicates they have completed at least 4 years of college education (U.S. data) or tertiary education (E.U. data), and as low-skill workers otherwise. The samples for the E.U. countries are dictated by data availability; the sample for the United States begins at the earliest year for which there is data available for the E.U. countries. We can see that in some cases – like in the Czech Republic, Finland, and Ireland – the standard deviation of the detrended log unemployment rate is around 10% to 15% larger for high-skill workers than for low-skill workers. In other cases – like in Austria, Germany or Hungary – the difference is much more substantial, with the standard deviation of the detrended log unemployment rate being at least 50% larger for high-skill workers. Across all

¹We present results obtained from data on unemployment rates, but there is no meaningful difference if we use data on unemployment levels.

TABLE 2.2: CYCLICAL VOLATILITY OF THE UNEMPLOYMENT RATE IN THE UNITED STATES, BY SKILL GROUP

Period	Low-skill workers	High-skill workers	Ratio high-low
1976:Q1–2016:Q4	11.80	12.94	1.10
1976:Q1–1983:Q4	14.57	12.55	0.86
1984:Q1–2016:Q4	11.03	13.05	1.18

Notes: The statistics reported are standard deviations (in percent). Data are log-transformed quarterly unemployment rates, presented as deviations from a Hodrick-Prescott filtered trend with the smoothing parameter set to 1600. Data are obtained from monthly series of the *Current Population Survey*. See the text for additional details.

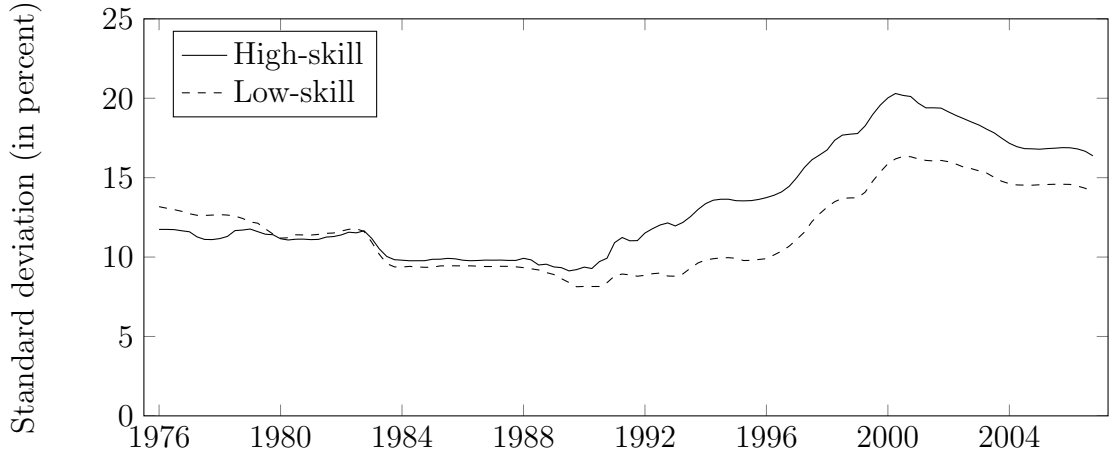
countries, the business cycle volatility of the unemployment rate is on average 37% higher for high-skill workers than for low-skill workers, and a Wilcoxon signed-rank test shows that the difference is statistically significant at the 1% level ($z = -3.296$, $p = 0.001$).²

For the United States the availability of data allows us to extend our analysis to a longer period of time, and in Table 2.2 we present additional evidence regarding the volatility gap in the detrended log unemployment rates of low-skill and high-skill workers. Over the period 1976:Q1–2016:Q4, the standard deviation of the unemployment rate is 10% larger for high-skill workers than for low-skill workers, a gap which is smaller than the 21% gap observed over the period 1998:Q1–2016:Q4. This suggests that the unemployment volatility gap in the United States experienced a change some time between the first quarter of 1976 and the last quarter of 2016. This is perhaps unsurprising, as the literature documents several instances of volatility shifts in time series of the United States economy during the mid-1980s. For example, Kim and Nelson (1999) and McConnell and Perez-Quiros (2000) provide evidence that points to a decline in the volatility of the growth rate of the U.S. GDP after the first quarter of 1984. Stock and Watson (2002) present evidence of similar declines in several other time series of the United States economy. More recently, Castro and Coen-Pirani (2008) document a threefold increase in the cyclical volatility of skilled hours relative to the cyclical volatility of GDP in the United States since 1984, and Champagne and Kurmann (2013) show that the business cycle volatility of the average real hourly wage increased at least 30% since 1984.

Accordingly, in Table 2.2 we also present results for two sub-periods of the U.S. data

²The difference between the standard deviations of the detrended log unemployment rates of high-skill and low-skill workers across countries remains statistically significant at the 1% level on a Wilcoxon signed-rank test ($z = -2.934$, $p = 0.0033$) even if we exclude the observations relative to France, Germany and Luxembourg – three countries for which the results are obtained from smaller samples and may therefore be less reliable.

FIGURE 2.1: CYCLICAL VOLATILITY OF THE UNEMPLOYMENT RATE IN THE UNITED STATES, 40-QUARTERS-AHEAD, BY SKILL GROUP



created by splitting the sample in the first quarter of 1984. In the 1976:Q1–1983:Q4 sub-period, the volatility of the detrended log unemployment rate is about 14% lower for high-skill workers than for low-skill workers. In contrast, in the 1984:Q1–2016:Q4 sub-period the detrended log unemployment rate is 18% more volatile for high-skill workers than for low-skill workers. The change is mostly driven by a decrease in the standard deviation for low-skill workers (from 14.57 to 11.03), as there is only a slight increase in the standard deviation for high-skill workers (from 12.55 to 13.05). In Figure 2.1 we offer another perspective of the change in the relative size of the cyclical volatilities of the unemployment rates of high-skill and low-skill workers. The lines depict 10-years-ahead rolling-window standard deviations of the detrended log unemployment rate. We can see that the forward volatility is initially lower for high-skill workers, but the gap relative to low-skill workers fades as we enter the 1980s, and by the mid-1980s the 10-years-ahead volatility is slightly higher for high-skill workers. The gap widens in the early and mid-1990s and remains large for the rest of the sample, with the 10-years-ahead volatility being 15% higher for high-skill workers than for low-skill workers at the end of the sample.

In this paper we generalize the framework proposed by Çenesiz and Guimarães (2017) to a context of two-skill groups, and we use this setup to address the differences in the cyclical volatility of the unemployment rates of high-skill and low-skill workers. We consider an economy in which households have a variety of high-skill and low-skill workers, each offering a specific skill from which monopolistic profits can be derived. Households bear the cost of searching and finding new jobs, and they decide how many new high-skill and low-skill jobs are created each period. While costly, expanding the labor supply on the extensive margin (i.e., employment) benefits the

household by increasing the number of skill varieties that yield monopolistic profits. On the production side, we assume that firms employ capital and a labor bundle that consists of hours of work from a variety of high-skill and low-skill workers. We assume that firms have a taste for variety with respect to their labor inputs, and this materializes in higher productivity when a wider array of skills is used.

Unemployment dynamics in our model are dictated by two forces. When a positive technology shock hits the economy both productivity and wages increase, raising the value of the marginal new (high-skill or low-skill) job from which the household may extract monopolistic profits. This allows households to offset the corresponding search costs for those new jobs, creating an incentive for employment to expand. On the firm side, employment expansion is also attractive because of the increasing returns to employment implied by the firm's taste for variety. In a calibration of our model to the United States data for the period 1976:Q1–2016:Q4, job search costs are relatively larger for high-skill workers than for low-skill workers. Yet, in the aftermath of a positive technology shock employment expansion relative to the steady state is similar for high-skill and low-skill workers. Higher unemployment rate volatility for high-skill workers then follows from their lower average unemployment rate.

The numerical simulations of the calibrated model generate a volatility of the unemployment rate that is 11.4% higher for high-skill workers than for low-skill workers, a difference that is close to the 9.6% difference observed in the data. Both results are robust to different calibrations of the Frisch elasticity, as well as to different calibrations of the parameter that governs the firms' taste for variety and the size of the monopolistic profits earned by households when exploiting each skill variety. However, our results indicate that the model cannot easily explain the shift in the volatility patterns of the unemployment rates that occurred in the United States during the mid-1980s and early 1990s.

Research that examines differences in the volatility of the unemployment between high-skill and low-skill workers is relatively scarce, but some studies consider the volatility gap in other contexts. Mukoyama and Şahin (2006) study differences in the costs of business cycles for high-skill and low-skill workers in a model with incomplete markets and skill heterogeneity, and conclude that the costs of business cycles are between three and ten times larger for unskilled workers. In their model, however, the transitions into and out of unemployment are determined exogenously, and imply higher volatility of the unemployment rate for low-skill workers. In contrast, in our model transitions out of unemployment are determined by the decisions of the

households with respect to job search, and thus unemployment volatility is determined endogenously. More recently, Hagedorn et al. (2016) introduce skill heterogeneity and capital-skill complementarity (as in Krusell et al., 2000) in a standard search and matching model to examine the effects of taxes on unemployment. They argue that capital-skill complementarity amplifies the volatility of productivity for high-skill workers, driving unemployment volatility upwards, and that higher taxes improve the relative productivity of low-skill, shifting rises in the unemployment to high-skill workers. In our model, unemployment volatility is instead amplified by the presence of economic gains associated with the expansion of employment – both for households, in the form of monopolistic profits over each skill variety, and for firms, in the form of a variety effect that increases productivity.

To some extent, our paper is also related to the literature on the unemployment volatility puzzle. In his influential contribution, Shimer (2005) shows that the business cycle volatility of U.S. unemployment is about 20 times larger than the business cycle volatility of unemployment generated by the Mortensen and Pissarides (1994) search and matching model. This finding has spawned a large literature that aims at improving the amplification mechanism of the search and matching framework. A set of studies argues that some form of wage rigidity is necessary to generate realistic unemployment fluctuations. A few examples of this line of research include the role bargaining delays emphasized by Hall and Milgrom (2008), the staggered wage bargaining proposed by Gertler and Trigari (2009), or the presence of information asymmetries proposed by Kennan (2010). Hagedorn and Manovskii (2008), on the other hand, argue that an alternative calibration for value of non-market activity and the workers' bargaining weight are sufficient to increase unemployment volatility on the canonical search and matching model. Pissarides (2009) emphasizes instead that fixed matching costs can increase the volatility of unemployment while retaining the wage flexibility for new matches observed in the data. More recently, Petrosky-Nadeau and Wasmer (2013) support Pissarides' view by arguing that financial frictions generate an entry cost to job creation, and that such cost increases volatility in the labor market.

Our paper makes a contribution to this discussion by introducing an alternative framework to model unemployment in an otherwise standard real business cycle model. Unlike the standard search and matching model, in which wage increases that occur in response to a positive shock discourage firms from creating jobs, the mechanisms in our model combine to favor employment expansion and amplify volatility in the labor market. On the firm side the variety effect raises productivity

when employment expands, offsetting the detrimental effects of wage increases on job creation. On the household side the expansion of employment increases the number of skill varieties from which monopolistic profits can be derived, offsetting the costs of searching for new jobs. The model calibrated for the period 1976:Q1–2016:Q1 generates realistic business cycle volatility for the U.S. unemployment rates. For high-skill workers the unemployment rate is about 9.4 times more volatile than output in the data, and about 8.9 times more volatile than output in the simulations of the model. For low-skill workers the unemployment rate is about 8.6 times more volatile than output in the data, and about 8.1 times more volatile than output in the simulations of the model.

The rest of the paper is organized as follows. In Section 2.2 we present the model and describe its competitive equilibrium. In Section 2.3 we discuss how we calibrate the model to United States data. In Section 2.4 we compare the results of our numerical simulations with the data. In Section 2.5 we perform a sensitivity analysis with respect to a set of key parameters. We close with some concluding remarks in Section 2.6.

2.2 Model

For ease of exposition and notation, in what follows we use the term *skilled* to refer to high-skill workers. We denote any variable that relates to skilled workers with the subscript s . Similarly, we use the term *unskilled* to refer to low-skill workers. We denote any variable that relates to unskilled workers with the subscript u . We assume that households live infinitely, and time is discrete and indexed by $t \geq 0$.

2.2.1 Firms

The technology of a representative firm is described by a Cobb-Douglas function:

$$y_t = a_t k_t^\alpha l_t^{1-\alpha}, \quad (2.1)$$

where y_t is the output of final goods, k_t is the capital input, l_t is the labor input, and a_t is a common productivity factor. The parameter α is the capital share, $0 < \alpha < 1$. The law of motion of the common productivity factor is given by:

$$\log a_t = \rho \log a_{t-1} + \epsilon_t, \quad (2.2)$$

where ϵ_t is an i.i.d. productivity shock, $\epsilon_t \sim N(0, \sigma_\epsilon)$ for all $t \geq 0$. The labor input l_t is a composite of skilled labor, $l_{s,t}$, and unskilled labor, $l_{u,t}$:

$$l_t = l_{s,t}^v l_{u,t}^{1-v}, \quad (2.3)$$

where $0 < v < 1$.

The input $l_{u,t}$ is a composite of hours of work, and is described by a constant elasticity of substitution function over a continuum of unskilled workers indexed by j :

$$l_{u,t} = \left[\int_{j \in J_{u,t}} h_{u,t}(j)^\theta dj \right]^{\frac{1}{\theta}}, \quad (2.4)$$

where $h_{u,t}(j)$ are the hours worked by the j -th unskilled worker, $J_{u,t}$ is the set of unskilled workers employed by the firm at time t , and $1/(1-\theta)$ is the elasticity of substitution between any two unskilled workers. Because our model features unemployment, $J_{u,t}$ is a subset of all existing unskilled workers, $J_{u,t} \subset J_u$. The input $l_{s,t}$ is defined in a similar way:

$$l_{s,t} = \left[\int_{j \in J_{s,t}} (\omega h_{s,t}(j))^\theta dj \right]^{\frac{1}{\theta}}, \quad (2.5)$$

where $h_{s,t}(j)$ are the hours worked by the j -th skilled worker, $J_{s,t} \subset J_s$ is the set of skilled workers employed by the firm at time t , and $1/(1-\theta)$ is the elasticity of substitution between any two skilled workers, $0 < \theta < 1$. The parameter $\omega > 1$ captures a productivity advantage of skilled workers relative to unskilled workers.

The firm sells its output in a perfectly competitive market, and – given the law of motion of the common productivity factor – it solves:

$$\max_{y_t, k_t, l_t, l_{u,t}, l_{s,t}, h_{u,t}(j), h_{s,t}(j)} y_t - r_t k_t - \int_{j \in J_{u,t}} w_{u,t}(j) h_{u,t}(j) dj - \int_{j \in J_{s,t}} w_{s,t}(j) h_{s,t}(j) dj, \quad (2.6)$$

subject to (2.1) and (2.3)–(2.5), where r_t is the rental rate of capital, $w_{u,t}(j)$ is the hourly wage paid to the j -th unskilled worker, and $w_{s,t}(j)$ is the hourly wage paid to the j -th skilled worker. The first order conditions of the firm's maximization problem imply:

$$r_t = \alpha \frac{y_t}{k_t} \quad (2.7)$$

$$W_{u,t} = \left[\int_{j \in J_{u,t}} w_{u,t}(j)^{\frac{\theta}{\theta-1}} dj \right]^{\frac{\theta-1}{\theta}} \quad (2.8)$$

$$W_{s,t} = \omega^{-1} \left[\int_{j \in J_{s,t}} w_{s,t}(j)^{\frac{\theta}{\theta-1}} dj \right]^{\frac{\theta-1}{\theta}} \quad (2.9)$$

$$W_{u,t} = (1 - \alpha) (1 - v) \frac{y_t}{l_{u,t}} \quad (2.10)$$

$$W_{s,t} = (1 - \alpha) v \frac{y_t}{l_{s,t}} \quad (2.11)$$

$$h_{u,t}(j) = \left[\frac{w_{u,t}(j)}{W_{u,t}} \right]^{\frac{1}{\theta-1}} l_{u,t} \quad (2.12)$$

$$h_{s,t}(j) = \left[\frac{w_{s,t}(j)}{W_{s,t}} \omega^{-\theta} \right]^{\frac{1}{\theta-1}} l_{s,t} \quad (2.13)$$

where $W_{u,t}$ is the unskilled wage index, as defined in (2.8), and $W_{s,t}$ is the skilled wage index, as defined in (2.9).

2.2.2 Households

The representative household is composed of a continuum of unskilled members of mass N^u , and a continuum of skilled members of mass N^s , with $N^u + N^s = 1$; both types of household members are indexed by a variety index j . At any given time t a fraction $n_{u,t} \in [0, N^u]$ of unskilled members and a fraction $n_{s,t} \in [0, N^s]$ of skilled members are employed. As in Merz (1995), household members pool their income as a mechanism to completely insure each other against unemployment. The period utility of the household is given by:

$$U_t = \log c_t - \int_0^{n_{u,t}} \chi_u \frac{(h_{u,t})^{1+\psi_u}}{1 + \psi_u} dj - \int_0^{n_{s,t}} \chi_s \frac{h_{s,t}(j)^{1+\psi_s}}{1 + \psi_s} dj, \quad (2.14)$$

where c_t is the consumption of the household, $1/\psi_s$ and $1/\psi_u$ are the Frisch elasticities of labor supply for skilled and unskilled household members, and χ_s and χ_u are measures of the disutility of work for skilled and unskilled household members.

At the end of any given period t a fraction of the household members who are employed lose their jobs. The household members who are unemployed engage in a costly search for new jobs, and thus $n_{u,t}$ and $n_{s,t}$ change over time in response to the interplay between job destruction and job creation. The law of motion of $n_{u,t}$ is

given by:

$$n_{u,t} = (1 - \delta_u) n_{u,t-1} + x_{u,t}, \quad (2.15)$$

where δ_u is the fraction of unskilled workers who lose their jobs, and $x_{u,t}$ are the new jobs for unskilled members at time t . Likewise, the law of motion of $n_{s,t}$ is given by:

$$n_{s,t} = (1 - \delta_s) n_{s,t-1} + x_{s,t}, \quad (2.16)$$

where δ_s is the fraction of unskilled workers who lose their jobs, and $x_{s,t}$ are the new jobs for unskilled members at time t . The laws of motion (2.15) and (2.16) imply that new jobs created at time t become immediately productive. In this economy, unskilled unemployment is given by $q_{u,t} = (N^u - n_{u,t})$, the skilled unemployment is given by $q_{s,t} = (N^s - n_{s,t})$, and aggregate unemployment is given by $q_t \equiv q_{s,t} + q_{u,t} = 1 - n_{s,t} - n_{u,t}$. The unemployment rates of skilled and unskilled workers are given by $u_{s,t} = \frac{q_{s,t}}{N^s}$ and $u_{u,t} = \frac{q_{u,t}}{N^u}$, respectively.

The household holds a stock of capital for which the law of motion is:

$$k_{t+1} = (1 - \delta_k) k_t + i_t, \quad (2.17)$$

where δ_k is the constant depreciation rate, and i_t is the household's investment.

The household spends its income on consumption, investment, and costly job searching activities for unskilled and skilled workers who are unemployed. The budget constrain of the household is given by:

$$c_t + i_t + g_{u,t}(x_{u,t}) + g_{s,t}(x_{s,t}) \leq \int_0^{n_{u,t}} w_{u,t}(j) h_{u,t}(j) dj + \int_0^{n_{s,t}} w_{s,t}(j) h_{s,t}(j) dj + r_{k,t} k_t, \quad (2.18)$$

where $g_{u,t}(x_{u,t})$ and $g_{s,t}(x_{s,t})$ are strictly increasing functions that measure the costs of finding unskilled and skilled jobs, respectively. We assume that these costs are quadratic in the number of new jobs created at time t :

$$g_{u,t}(x_{u,t}) = \phi_u \left(x_{u,t} + \frac{1}{2} x_{u,t}^2 \right) \quad (2.19)$$

$$g_{s,t}(x_{s,t}) = \phi_s \left(x_{s,t} + \frac{1}{2} x_{s,t}^2 \right) \quad (2.20)$$

with $\phi_u, \phi_s > 0$.

The household solves:

$$\max_{c_t, k_{t+1}, n_{u,t}, n_{s,t}, h_{u,t}(j), h_{s,t}(j), w_{u,t}(j), w_{s,t}(j)} E_0 \sum_{t=0}^{\infty} \beta^t U_t \quad (2.21)$$

subject to (2.12)–(2.13) and (2.15)–(2.20), where β is the common discount factor in the economy. We anticipate an equilibrium in which there is symmetry across unskilled workers, and symmetry across skilled workers. For unskilled workers we have $w_{u,t}(j) = w_{u,t}$ and $h_{u,t}(j) = h_{u,t}$, $\forall j \in [0, n_{u,t}]$; for skilled workers we have $w_{s,t}(j) = w_{s,t}$ and $h_{s,t}(j) = h_{s,t}$, $\forall j \in [0, n_{s,t}]$. The first order conditions of the household's maximization problem imply:

$$1 = \beta E_t \left[\frac{c_t}{c_{t+1}} (1 - \delta_k + r_{k,t+1}) \right] \quad (2.22)$$

$$w_{u,t} = c_t h_{u,t}^{\psi_u} \frac{\chi_u}{\theta} \quad (2.23)$$

$$w_{s,t} = c_t h_{s,t}^{\psi_s} \frac{\chi_s}{\theta} \quad (2.24)$$

$$g'_{u,t}(x_{u,t}) = w_{u,t} h_{u,t} \frac{1 + \psi_u - \theta}{1 + \psi_u} + E_t \left[\beta (1 - \delta_u) \frac{c_t}{c_{t+1}} g'_{u,t}(x_{u,t+1}) \right] \quad (2.25)$$

$$g'_{s,t}(x_{s,t}) = w_{s,t} h_{s,t} \frac{1 + \psi_s - \theta}{1 + \psi_s} + E_t \left[\beta (1 - \delta_s) \frac{c_t}{c_{t+1}} g'_{s,t}(x_{s,t+1}) \right] \quad (2.26)$$

where $g'_{u,t} = \partial g_{u,t} / \partial x_{u,t}$ and $g'_{s,t} = \partial g_{s,t} / \partial x_{s,t}$, $\forall t \geq 0$.

An aggregate resource constraint closes the model of the economy:

$$c_t + i_t + g_{u,t}(x_{u,t}) + g_{s,t}(x_{s,t}) \leq y_t. \quad (2.27)$$

2.2.3 Competitive equilibrium

A competitive equilibrium for this economy is a sequence of prices $\{r_t, w_t^s, w_t^u\}_{t=0}^{\infty}$ and allocations $\{y_t, c_t, k_{t+1}, l_t, l_{s,t}, l_{u,t}, n_{u,t}, n_{s,t}, x_{u,t}, x_{s,t}\}_{t=0}^{\infty}$ such that firms solve (2.6) subject to 2.1 and 2.3–2.5, households solve (2.21) subject to (2.12)–(2.13) and (2.15)–(2.20), the aggregate resource constraint binds, and:

$$l_{u,t} = \left[\int_0^{n_{u,t}} h_{u,t}(j)^\theta dj \right]^{\frac{1}{\theta}}$$

$$l_{s,t} = \left[\int_0^{n_{s,t}} (\omega h_{s,t}(j))^\theta dj \right]^{\frac{1}{\theta}}$$

given the exogenous process for the common productivity factor described in (2.2). In the symmetric competitive equilibrium the unskilled and skilled labor inputs used by the firm and the

$$l_{u,t} = h_{u,t} (n_{u,t})^{\frac{1}{\theta}} \quad (2.28)$$

$$l_{s,t} = \omega h_{s,t} (n_{s,t})^{\frac{1}{\theta}} \quad (2.29)$$

$$W_{u,t} = w_{u,t} (n_{u,t})^{\frac{\theta-1}{\theta}} \quad (2.30)$$

$$W_{s,t} = \omega^{-1} w_{s,t} (n_{s,t})^{\frac{\theta-1}{\theta}}. \quad (2.31)$$

The results (2.28) and (2.29) highlight how the assumption that firms have a taste for skill variety within each skill group leads to increasing returns to scale in the unskilled and skilled labor inputs.

2.3 Calibration

In this section we describe the baseline calibration used in our numerical simulations. We calibrate the model to United States data and define the quarter as the unit of time. Table 2.3 summarizes the baseline parameter values. For some of the parameters we use values that are standard in the business cycle literature. We set the capital share α to 0.36. We set the discount factor β to 0.99 so that annual interest rate is 4% in the steady state. We set the depreciation rate δ_k to 0.025 so that capital depreciation approximates 10% annually. Finally, for the law of motion of technology we use $\sigma_\epsilon = 0.007$ and $\rho = 0.95$.

For the inverse of the Frisch elasticities our baseline calibration considers $\psi_s = \psi_u = 1.5$, which implies Frisch elasticities of 0.67 for both skilled and unskilled workers. There is considerable debate about the value of the Frisch elasticity: studies based on microeconomic data typically yield estimates well below 1, while macroeconomic models often require values in excess of 2 to match the business cycle volatility observed in the data (see, e.g., Chetty et al. (2011) for a discussion of the mismatch between micro and macro estimates). Given this lack of consensus and considering that the behavior of the labor market variables is likely to be affected by the Frisch elasticities, in Section 2.5 we include ψ_s and ψ_u in our sensitivity analysis.

To calibrate the separation rates δ_u and δ_s we turn to empirical estimates available

in the literature. Chassamboulli (2011) estimates monthly separation rates using data from the *Job Openings and Labor Turnover Survey* covering the period between December 2000 and October 2010, finding a separation rate of 0.016 for high-skill workers and a separation rate of 0.035 for low-skill workers. At quarterly frequency these estimates imply a separation rate of 0.047 for high-skill workers and a separation rate of 0.101 for low-skill workers. More recently, Hagedorn et al. (2016) estimate monthly separation rates using data from the *Current Population Survey* covering the period between January 1976 and December 2006 and obtain similar results. Their estimates indicate a separation rate of 0.0097 for high-skill workers and a separation rate of 0.0378 for low-skill workers. At quarterly frequency these estimates imply a separation rate of 0.029 for high-skill workers and a separation rate of 0.109 for low-skill workers. We consider an average of these two estimates and set $\delta_s = 0.038$ and $\delta_u = 0.105$. In our model these values imply that in any given quarter 3.8% of the skilled workers and 10.5% of the unskilled workers lose their jobs.

We set $v = 0.4$ so that skilled workers receive 40% of the total wage bill. This number is consistent with estimates available in the literature for the share of the wage bill earned by high-skill workers. For example, Machin and Van Reenen (1998) show that in the United States the share of the wage bill paid to non-production workers (a proxy for high-skill workers) was 41.4% in 1989. More recently Chongvilaivan et al. (2009) show that, according to data from the *2002 Annual Survey of Manufactures* published by the U.S. Census Bureau, high-skill workers receive 39.9% of the wage bill.

For the productivity advantage of skilled workers relative to unskilled workers, ω , we turn to estimates from the literature on skill-related wage differences. For example, Katz and Murphy (1992) show that the wage premium of college educated workers (a proxy for high-skill workers) in the U.S. was between 50% and 70% relative to non-college educated workers during the period between the early 1960s to the late 1980s. In another study, Berman et al. (1998) find that the wages of non-production workers (a proxy for high-skill workers) are about 50% higher than the wages of production workers (a proxy for low-skill workers) in OECD countries. More recently, van der Velden and Bijlsma (2016) estimate that in a sample of 22 OECD countries workers with a college degree earn, on average, almost 30% more than workers without a college degree. To the extent that differences in wages reflect differences in worker productivity, these estimates would suggest that the productivity advantage of skilled workers relative to unskilled workers is between 30% and 70%. Accordingly, in our baseline calibration we set $\omega = 1.5$.

TABLE 2.3: BASELINE CALIBRATION

Description	Parameter	Value
Firms:		
Capital's income share	α	0.36
Capital depreciation rate	δ_k	0.025
Productivity advantage of skilled workers	ω	1.5
Skilled workers' wage bill share	v	0.40
Elasticity of substitution between workers of same type	$1/(1 - \theta)$	6.67
Households:		
Discount factor	β	0.99
Inverse of the Frisch elasticity	ψ_s, ψ_u	1.5
Separation rate for skilled workers	δ_s	0.038
Separation rate for unskilled workers	δ_u	0.105
Search cost parameter for skilled jobs	ϕ_s	25.7
Search cost parameter for unskilled jobs	ϕ_u	5.1
Scaling of disutility from skilled work	χ_s	2.4
Scaling of disutility from unskilled work	χ_u	1.2
Technology:		
Standard deviation of technology shock	σ_ϵ	0.007
Persistence of the technology process	ρ	0.95

For the parameter θ there are no obvious empirical estimates available in the literature. In our baseline calibration we set $\theta = 0.85$, which implies an elasticity of substitution of 6.7 between any two workers in the same skill group, and in Section 2.5 we include this parameter in our sensitivity analysis. We use the remaining four parameters (χ_s , χ_u , ϕ_s , and ϕ_u) to normalize hours worked to one for both skilled and unskilled workers, and to target the average unemployment rates of skilled and unskilled workers in the United States in the period 1976:Q1–2016:Q4, which are 2.9% and 6.8%, respectively.³ This yields the calibration $\chi_s = 2.4$, $\chi_u = 1.2$, $\phi_s = 25.7$, and $\phi_u = 5.1$. This calibration implies that households face job search costs that are higher for skilled workers than for unskilled workers. Intuitively, this is a reasonable assumption: skilled jobs are likely to be more complex than unskilled jobs, and skilled workers are likely to be required to go through more rounds of screening than unskilled workers to ensure a correct match to a new job, resulting in higher search costs for skilled workers.

³The Appendix illustrates how we use the hours normalization and our target unemployment rates to pin down χ_s , χ_u , ϕ_s , and ϕ_u .

2.4 Results

2.4.1 Business cycle properties

In this section we compare the business cycle properties of the calibrated model with the business cycle properties of U.S. data covering the period 1976:Q1–2016:Q4. While our focus is on the volatility of the unemployment rates of skilled and unskilled workers, we also examine the behavior of other macroeconomic aggregates. We run 1000 model simulations of as many quarters as in the U.S. sample (164 quarters), and for each simulation we compute standard deviations, autocorrelations, and cross-correlations (with output) for the unemployment rates, output, consumption and investment. The results we report for the model are the means of the simulated statistics. To compute the equivalent statistics for the U.S. economy we use data on output, consumption and investment published by the *Bureau of Economic Analysis*, and data on the unemployment rates computed from monthly series of the *Current Population Survey*. All variables are log-transformed and presented as deviations from a Hodrick-Prescott filtered trend with the smoothing parameter set to 1600. We present the results in Table 2.4.

The calibrated model replicates the business cycle volatility of the unemployment rates quite well. The simulated standard deviation of the unemployment rate is 12.70 for skilled workers and 11.44 for unskilled workers, a difference that makes the business cycle volatility 11% larger for skilled workers. In the data, the standard deviation of the unemployment rate is 12.94 for skilled workers and 11.80 for unskilled workers, a difference that makes the business cycle volatility around 10% larger for skilled workers. Moreover, in the model the unemployment rates are substantially more volatile than output, and the volatility ratios are close to those we observe in the data. For skilled workers, the unemployment rate is 8.9 times more volatile than output in our simulations, and 9.4 times more volatile than output in the data. For unskilled workers, the unemployment rate is 8.1 times more volatile than output in our simulations, and 8.6 times more volatile than output in the data. Thus, in terms of the business cycle volatility of unemployment our model outperforms the canonical search and matching model of Mortensen and Pissarides (1994).

The model also generates realistic business cycle volatility for the time series of output and investment. The simulated standard deviations of output and investment are 1.42 and 5.01, respectively, whereas the corresponding standard deviations in the data are 1.37 and 4.71. Even though the model slightly overestimates the volatility of

TABLE 2.4: STANDARD DEVIATIONS, AUTOCORRELATIONS AND CROSS CORRELATIONS WITH OUTPUT, FROM MODEL SIMULATIONS AND U.S. DATA, 1976:Q1–2016:Q4

	Standard deviation					Autocorrelation					Correlation with y			
	y	c	i	u_s	u_u	y	c	i	u_s	u_u	c	i	u_s	u_u
Model	1.42	0.32	5.01	12.70	11.44	0.69	0.83	0.28	0.81	0.82	0.77	0.08	-0.84	-0.95
Data	1.37	1.11	4.71	12.94	11.80	0.88	0.89	0.92	0.89	0.92	0.87	0.90	-0.80	-0.88

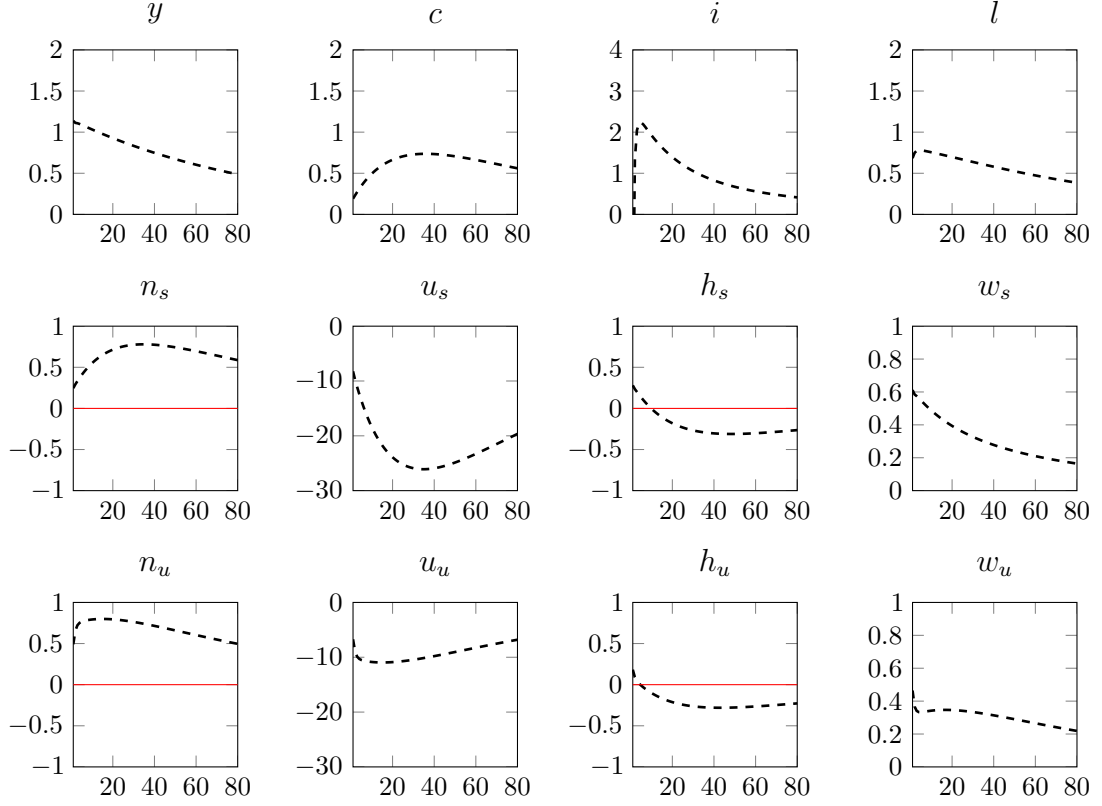
Notes: Standard deviations are in percent. The row labelled “Data” refers to United States quarterly data for the period 1976:Q1–2016:Q4. The series for output (y), consumption (c) and investment (i) are from the Bureau of Economic Analysis. The series for the quarterly unemployment rates (u_s , u_u) are computed from monthly series of the *Current Population Survey*. The row labelled “Model” refers to results from 1000 model simulations of 164 quarters each, which is the same number of quarters as in the U.S. sample. The results are sample means of the statistics computed for each of the 1000 simulations. All variables are log-transformed and presented as deviations from a Hodrick-Prescott filtered trend with the smoothing parameter set to 1600.

both variables, it approximates the relative volatility of investment remarkably well: the time series for investment is 3.5 more volatile than output in the model, and 3.4 times more volatile than output in the data. One shortcoming of our model is that it generates time series for consumption that are too smooth. The simulated standard deviation of consumption is 0.32, whereas in the data the standard deviation is 1.11, about 3.5 times larger.

Turning to the simulated first-order autocorrelation coefficients, we see that for all variables presented in Table 2.4 the model generates coefficients that are smaller than those we estimate from the data. The model performs best when replicating the autocorrelation of the unemployment rates and consumption. For the unemployment rates of skilled and unskilled workers the simulated autocorrelation coefficients are 0.81 and 0.82, respectively, and for consumption the coefficient is 0.83. In all three cases the simulated coefficients are about 10% smaller than the corresponding coefficients estimated from the data. The model performs worse when replicating the autocorrelation of output and investment. The simulated autocorrelation coefficients are 0.69 for output and 0.28 for investment, whereas in the data the coefficients are 0.88 and 0.92. The difference is particularly striking for investment, with the coefficient estimated from the data being 3.3 times larger than the simulated coefficient. Furthermore, the autocorrelation of the simulated time series is much smaller for investment than for output, whereas in the data the autocorrelation coefficient is slightly larger for investment than for output.

The model generates reasonable cross correlations between output and the unemployment rates. For skilled workers the cross correlation is -0.84 in the model and -0.80 in the data. For unskilled workers the cross correlation is -0.95 in the model and -0.88 in the data. Although the simulated cross correlations are between 5% and 8% larger than what we observe in the data, the model correctly generates a cross correlation between output and the unemployment rate that is larger for unskilled workers. The simulated co-movement of output and consumption is also plausible, with the model generating a cross correlation of 0.77 between the two variables, a figure that is about 12% smaller than its equivalent in the data. However, the model performs poorly in terms of the cross correlation between output and investment. In the data the two variables exhibit very tight co-movement, but in the calibrated model we obtain a very small positive cross correlation.

FIGURE 2.2: RESPONSE OF SELECTED MODEL VARIABLES TO AN EXOGENOUS TECHNOLOGY SHOCK



Notes: The dashed lines represent the response of selected model variables to a one standard deviation ($\sigma_\epsilon = 0.007$) exogenous technology shock. The horizontal axis measures the number of periods after the shock. All variables are presented as percent deviations from their respective steady state values.

2.4.2 Impulse response functions

We now analyze how a set of model variables behave in response to an exogenous technology shock. In Figure 2.2 we depict the response of output, consumption, investment, employment, unemployment, hours worked, and wages to a one standard deviation positive technology shock in our calibrated model. All variables as presented as percent deviations from their steady state values. In the top three panels, we see that the shock produces the usual effects on output, consumption and investment: all three variables increase after the shock hits the economy, and then gradually return to their steady state values. Thus, with respect to these variables our model essentially retains the responses typically observed in a standard business cycle model.

When the shock hits the economy, skilled employment initially increases less than

unskilled employment because the cost of searching for new jobs is relatively higher for skilled workers than for unskilled workers. This initial expansion in employment gives rise to the variety effect on the firms' side and contributes to increase productivity. This, in turn, drives further employment expansions by making the marginal new job (skilled or unskilled) valuable enough to offset the respective search cost. Because of the complementarity between skilled and unskilled labor in the firms' labor bundle, the expansion of unskilled employment increases the productivity of skilled workers. As a result, more new skilled jobs are now valuable enough to offset their corresponding search costs, and additional expansions of skilled employment become economically attractive for the households. While the same effect exists for unskilled workers, the strong initial expansion driven by the lower search costs reduces the scope for additional employment growth. These dynamics cause skilled employment to peak later than unskilled employment, although they both expand by around 0.8% relative to their steady state values.

Because the unemployment rate of skilled workers is lower than the employment rate of unskilled workers, the employment growth results in a stronger compression of the unemployment rate for skilled workers than for unskilled workers. At the peak of skilled employment expansion, the unemployment rate for skilled workers is compressed by around 26% relative to its steady state value. In contrast, at the peak of unskilled employment expansion, the unemployment rate for unskilled workers is compressed by only 11% relative to its steady state value.

When the exogenous shock hits the economy, hours worked increase for skilled and unskilled workers. The productivity shock increases the value of market work and creates an incentive to substitute leisure for labor. As employment expands, the number of skill varieties from which households derive monopolistic profits increases, and the resulting gains allow households to shift part of the labor supply from the intensive margin (hours) to the extensive margin (employment). The initial increase in hours is slightly larger for skilled workers: relative to the steady state, skilled hours expand by as much as 0.28%, whereas unskilled hours expand by as much as 0.18%. Wages respond to the exogenous shock with a profile similar to that of output, increasing when the shock hits the economy and then gradually converging back to their steady state value. For unskilled workers, the stronger employment expansion immediately after the shock is associated with a steeper compression of the wages early on, but smoother declines in subsequent periods.

2.4.3 Unemployment rate volatility: pre-1984 and post-1984

2.4.3.1 Baseline simulations

In Section 2.1 we have seen that, starting in the mid-1980s, the business cycle volatility of the U.S unemployment rates experienced some changes. The unemployment rate was slightly more volatile for low-skill workers than for high-skill workers in the 1976:Q1–1983:Q4 sub-period, but more volatile for high-skill workers in the 1984:Q1–2016:Q4 sub-period. These patterns of volatility take place against different labor market conditions. The first difference, although small, pertains to the unemployment rates themselves. In the pre-1984 sub-period the unemployment rates averaged 2.9% for high-skill workers and 6.7% for low-skill workers; in the post-1984 sub-period they averaged 3.1% for high-skill workers and 7.5% for low-skill workers. The second difference, much more substantial, pertains to the share of high-skill workers in the labor force. In the pre-1984 sub-period the share of high-skill workers in the labor force averaged 17.2%, whereas in the post-1984 sub-period that share averaged 26%.

In this section we investigate whether our calibrated model can replicate the different patterns of volatility of the unemployment rates in the pre-1984 and post-1984 sub-periods. We proceed as before: we run 1000 simulations of as many quarters as in the relevant sub-period (32 quarters in 1976:Q1–1983:Q4, 132 quarters in 1984:Q1–2013:Q4), and for each of the simulations we compute standard deviations, autocorrelations, and cross correlations (with output) for the unemployment rates, output, consumption and investment. We then compute the sample means of the statistics obtained in each of the 1000 simulations, and we compare them to the corresponding statistics computed from the U.S. data. In all simulations we retain the baseline calibration summarized in Table 2.3, except for χ_s , χ_u , ϕ_s , and ϕ_u , which we use to normalize hours worked to one and to target the unemployment rates observed in each of the simulated sub-periods.

We present the results of our analysis in Table 2.5. On the simulations for the sub-period 1976:Q1–1983:Q4, the model generates unemployment rates that are more volatile for skilled workers than for unskilled workers, with the standard deviation being about 20% larger for skilled workers. This is in clear contradiction with the U.S. data, which show the business cycle volatility of the unemployment rate to be about 14% lower for skilled workers during that period. On the simulations for the sub-period 1984:Q1–2016:Q4, the model correctly generates a volatility for the

unemployment rates that is higher for skilled workers than for unskilled workers. However, the simulated volatility gap is about 8%, whereas in the data the volatility gap is about 18%. Moving between sub-periods, the model correctly replicates the increase in the volatility of the unemployment rate of skilled workers, but fails to account for the decrease in the volatility of the unemployment rate of unskilled workers.

For both periods our simulations generate time series that are more volatile for investment than for output. For the sub-period 1976:Q1–1983:Q4 the model yields a volatility ratio of 3.8, exceeding the ratio observed in the data by about 36%. For the period 1984:Q1–2016:Q4 the model performs slightly better, yielding a volatility ratio that is about 13% smaller than the ratio observed in the data. As before, consumption is much smoother in the model than in the U.S. data. For both periods the model simulations yield a volatility for consumption that is about 22% of the volatility of output, whereas in the data the volatility of consumption is between 76% and 85% of the volatility of output. One important mismatch is that, in general, the calibrated model yields lower levels of volatility for output, consumption and investment on the simulations for the 1976:Q1–1983:Q4 sub-period. In contrast, the data show that, in general, the volatility in 1976:Q1–1983:Q4 sub-period is actually higher than in the 1984:Q1–2016:Q4 sub-period. The results, however, are from simulations where the standard deviation of the exogenous technology shock is assumed to remain constant across the two sub-periods, and in light of the evidence presented in the literature (see, e.g., Kim and Nelson, 1999) this assumption might be somewhat problematic.

All variables exhibit a lower first-order autocorrelation on the simulations that correspond to the 1976:Q1–1983:Q4 sub-period. For output, consumption, and the unemployment rates, however, the data show that autocorrelations coefficients are only marginally smaller during this sub-period when compared to the post-1984 sub-period. For investment, the results from the model are a qualitative approximation to the data, although the simulated autocorrelation coefficients are substantially smaller than the equivalent coefficients in the data.

Except for investment, the cross correlations with output are not substantially different across the two sub-periods, both in the calibrated model and in the data. The model generates negative correlations between the unemployment rates and output that approximate the data quite well, and it yields a positive correlation between consumption and output that is only slightly smaller than in the data. As before, the model performs poorly in terms of replicating the correlation between investment and output. For the 1984:Q1–2016:Q4 sub-period the model predicts a

TABLE 2.5: STANDARD DEVIATIONS, AUTOCORRELATIONS AND CROSS CORRELATIONS WITH OUTPUT, FROM MODEL SIMULATIONS AND U.S. DATA, SUB-PERIOD ANALYSIS

	Standard deviation				Autocorrelation				Correlation with y			
	y	c	i	u_s	y	c	i	u_s	c	i	u_s	u_u
1976:Q1–1983:Q4												
Model	1.28	0.28	4.84	10.69	8.90	0.59	0.75	0.18	0.69	0.75	0.79	-0.03
Data	2.21	1.68	6.12	12.55	14.57	0.87	0.88	0.89	0.85	0.91	0.86	0.95
1984:Q1–2016:Q4												
Model	1.43	0.32	5.01	12.67	11.68	0.69	0.83	0.29	0.81	0.82	0.77	0.08
Data	1.07	0.91	4.29	13.05	11.03	0.89	0.89	0.94	0.89	0.93	0.88	0.89

Notes: Standard deviations are in percent. The row labelled “Data” refers to United States quarterly data. The series for output (y), consumption (c) and investment (i) are from the Bureau of Economic Analysis. The series for the unemployment rates (u_s , u_u) are computed from monthly series of the *Current Population Survey*. The row labelled “Model” refers to results from 1000 model simulations of as many quarters as in the U.S. samples (32 quarters in 1976:Q1–1983:Q4; 132 quarters in 1984:Q1–2016:Q4). The results are sample means of the statistics computed for each of the 1000 simulations. All variables are log-transformed and presented as deviations from a Hodrick-Prescott filtered trend with the smoothing parameter set to 1600.

positive cross-correlation that is much smaller than the correlation observed in the data. For the 1976:Q1–1983:Q4 sub-period the mismatch is more severe, with the model yielding a small negative correlation, whereas in the data the correlation is strongly positive.

With some exceptions, the results presented in this section show that adjusting our baseline calibration to account for differences in the relative supply of skilled workers and in the average unemployment rates across the pre-1984 and post-1984 sub-periods is insufficient to replicate certain features of the U.S. data. Some of the shortcomings of our simulations – such as the failure to replicate the lower volatility of output, consumption and investment in the 1984:Q1–2016:Q4 sub-period – are likely to be unrelated to the key feature of our model (i.e., the framework proposed to model unemployment). Other shortcomings – such as the failure to account for the change in the volatility gap of the unemployment rates of skilled and unskilled workers – speak to the core of our model and therefore warrant further examination.

2.4.3.2 Changing parameter calibration

For the purposes of our study, the key shortcoming of the sub-period simulations lies in the failure to fully account for the changes in the volatility of the unemployment rates. In this section we investigate whether the issue is amenable to different calibrations of θ , the parameter which is at the core of our framework to model unemployment. This parameter influences how strong the “taste for variety” is on the firm side, and how large are the monopoly gains that households can extract from each specific skill variety. We examine to what extent a different calibration for θ in each of the sub-periods contributes to improve the fit between the simulations and the U.S. data. As before, we retain the baseline calibration summarized in Table 2.3 for all other parameters except for χ_s , χ_u , ϕ_s , and ϕ_u , which we once again use to normalize hours worked to one, and to target the unemployment rates observed in each of the simulated sub-periods.

In Table 2.6 we report results from simulations in which we set $\theta = 0.75$ for the sub-period 1976:Q1–1983:Q4, and $\theta = 0.95$ for the sub-period 1984:Q1–2016:Q4. For the sub-period 1976:Q1–1983:Q4 the model continues to generate unemployment rates that are more volatile for skilled workers than for unskilled workers, in contrast with the data, although the simulated volatility gap (16%) is somewhat smaller than in our baseline results. For the sub-period 1984:Q1–2016:Q4 the model continues

to generate higher volatility on the unemployment rate of skilled workers, with the volatility being now about 12% larger relative to the volatility of unemployment rate of unskilled workers, providing a better approximation to the 18% gap observed in the data. Thus, the calibration with a variable θ contributes to improve the fit between the model and the U.S. data in terms of the business cycle volatility of the unemployment rates, although it does not eliminate the fundamental mismatch recorded in the 1976:Q1–1983:Q4 sub-period.

The new calibrations also improve the results for the business cycle volatility of output, consumption and investment. In general, the simulated volatility for the 1976:Q1–1983:Q4 sub-period is now higher, and the simulated volatility for the 1984:Q1–2016:Q4 sub-period is now lower. Not only are the simulated standard deviations closer to its empirical equivalents, but the model now correctly yields a decrease in the volatility of consumption and investment from the pre-1984 sub-period to the post-1984 sub-period. For output the calibrated model still predicts volatility to be higher in the sub-period 1984:Q1–2016:Q4, although the increase is of a much smaller magnitude than in our baseline results. With respect to the simulated first-order autocorrelations and cross-correlations with output the new calibrations yield results that are identical to our baseline results for the sub-period analysis.

The results suggest that while a calibration in which θ varies across sub-periods contributes to improve the fit between the simulations and the U.S. data, certain differences are still difficult to rationalize within the framework we propose. In particular, accounting for the change in the volatility patterns of the unemployment rates that occurred in the mid-1980s and early 1990s remains a challenge.

2.5 Sensitivity analysis

We now examine the results generated by our model under different calibrations for θ and for the inverse of the Frisch elasticities, ψ_s and ψ_u . We concentrate on these parameters because they are directly related to the labor market decisions of firms and households, and because they are either not standard in the literature, as is the case for θ , or there is considerable debate about their value, as is the case for ψ_s and ψ_u . Our simulations show that calibrations involving small values of θ (e.g., $\theta = 0.35$) yield unreasonably large standard deviations, time series for investment that exhibit negative autocorrelation and negative cross-correlation with output, as well

TABLE 2.6: STANDARD DEVIATIONS, AUTOCORRELATIONS AND CROSS CORRELATIONS WITH OUTPUT, FROM MODEL SIMULATIONS AND U.S. DATA, SUB-SAMPLE ANALYSIS

	Standard deviation					Autocorrelation					Correlation with y				
	y	c	i	u_s	u_u	y	c	i	u_s	u_u	c	i	u_s	u_u	
1976:Q1–1983:Q4															
Model	1.34	0.32	5.17	10.78	9.29	0.59	0.73	0.18	0.71	0.76	0.82	-0.06	-0.85	-0.94	
Data	2.21	1.68	6.12	12.55	14.58	0.87	0.88	0.89	0.85	0.91	0.86	0.95	-0.84	-0.95	
1984:Q1–2016:Q4															
Model	1.37	0.30	4.66	12.57	11.25	0.68	0.84	0.31	0.80	0.82	0.76	0.12	-0.85	-0.95	
Data	1.07	0.91	4.29	13.05	11.03	0.89	0.89	0.94	0.89	0.93	0.88	0.89	-0.85	-0.87	

Notes: Standard deviations are in percent. The row labelled “Data” refers to United States quarterly data. The series for output (y), consumption (c) and investment (i) are from the *Bureau of Economic Analysis*. The series for the unemployment rates (u_s , u_u) are computed from monthly series of the *Current Population Survey*. The row labelled “Model” refers to results from 1000 model simulations of as many quarters as in the U.S. samples (32 quarters in 1976:Q1–1983:Q4; 132 quarters in 1984:Q1–2016:Q4). The results are sample means of the statistics computed for each of the 1000 simulations. All variables are log-transformed and presented as deviations from a Hodrick-Prescott filtered trend with the smoothing parameter set to 1600.

as counterfactual impulse responses functions. This is an indication that our results do not hold with calibrations that involve small values for θ , and for that reason we concentrate on the higher end of the range of admissible values for θ . We present results from calibrations involving $\theta = \{0.75, 0.85, 0.95\}$ and $\psi_s, \psi_u = \{0.3, 1, 1.5\}$, and we restrict our attention to the cases in which $\psi_s = \psi_u$. Our baseline calibration ($\theta = 0.85$ and $\psi_s, \psi_u = 1.5$) is thus included in this sensitivity analysis for reference purposes.

In Table 2.7 we summarize the results of our sensitivity analysis, which for the sake of brevity we build only for simulations of the full U.S. sample (1976:Q1–2016:Q4). For each combination of parameters the results are mean statistics from 1000 model simulations of as many quarters as in the U.S. data (164 quarters). We see that, for any given value of the Frisch elasticities, the results are relatively stable with respect to the changes in the value of θ . Larger values of θ are typically associated with a lower volatility of the unemployment rates, reflecting the fact that larger values of θ imply a weaker variety effect on the firm side, and lower monopolistic profits on each specific skill variety on the household side. These two effects combine to decrease the attractiveness of expanding employment in response to an exogenous technology shock, hence the lower volatility of the unemployment rates.

Output, investment and consumption all exhibit lower volatility with larger values for θ , but in general the differences across simulations amount to less than 15% of the respective simulated standard deviations. One important result is that, for any given calibration of the Frisch elasticities, the ratio between the volatility of the unemployment rates and the volatility of output is quite robust to the value of θ . For unskilled workers, there is a 2% difference in the volatility ratios obtained with $\theta = 0.65$ and with $\theta = 0.95$. For skilled workers, the difference in the volatility ratios obtained with $\theta = 0.65$ and with $\theta = 0.95$ is somewhat larger, ranging from about 7% when $\psi_s, \psi_u = 1.5$ to about 11% when $\psi_s, \psi_u = 0.5$. In all cases, the simulated ratios provide a good approximation to the data. The unemployment rate of skilled workers is between 8.6 and 10.9 times more volatile than output in the model, and 9.4 times more volatile than output in the data. The unemployment rate of unskilled workers is between 8.0 and 8.32 times more volatile than output in the model, and 8.6 times more volatile than output in the data.

For the most part, the simulated autocorrelation coefficients and cross-correlations with output are very stable over the range of θ covered in our sensitivity analysis. There are, however, two exceptions worth mentioning. First, decreases in θ are associated with decreases in the first-order autocorrelation of investment, particularly

in calibrations with low values for ψ_s and ψ_u . Second, decreases in θ are associated with decreases in the cross-correlation between investment and output, with the sensibility to θ being again higher in calibrations with low values for ψ_s and ψ_u .

Turning to the effects of ψ_s and ψ_u , we see that for any given value of θ the simulated volatility of output and the unemployment rates is higher on calibrations with low values for ψ_s and ψ_u (i.e., high Frisch elasticities). On the other hand, the volatility of consumption and investment is lower on calibrations with low values for ψ_s and ψ_u . Calibrations with higher values for ψ_s and ψ_u also provide a better approximation for the relative volatility of investment: with $\psi_s, \psi_u = 0.5$ investment is between 2.5 and 2.8 times more volatile than output, whereas with $\psi_s, \psi_u = 1.5$ the ratio increases to around 3.5, very close to the 3.4 ratio in the data. Overall, for any given value of θ higher values of ψ_s and ψ_u seem to provide the best fit between the model and the data, indicating that our model works well with Frisch elasticities similar to those estimated from microeconomic data.

From a qualitative perspective, the results for the volatility of the unemployment rates are robust to the value of ψ_s and ψ_u : the unemployment rate of skilled workers is always more volatile than the unemployment rate of unskilled workers. From a quantitative perspective, higher values of ψ_s and ψ_u generate standard deviations for the unemployment rates that are closer to the data. The ratios between the volatility of the unemployment rates and output are also quite stable across different values of ψ_s and ψ_u . For skilled workers the calibrations with $\psi_s, \psi_u = 0.5$ yield unemployment rates that more volatile than output by a factor of around 10, whereas in calibrations with $\psi_s, \psi_u = 1.5$ the simulated volatility ratios are around 9 (in the data the ratio is 9.4). For unskilled workers the volatility ratios relative to output sit on a narrower range, with the simulations presented in Table yielding values between 8 and 8.3 (in the data the ratio is 8.6).

As was the case with θ , the simulated autocorrelation coefficients and cross-correlations with output are stable over the range of values of the Frisch elasticities covered in our sensitivity analysis. Once again, the exceptions are the first-order autocorrelation of investment and the cross-correlation between investment and output, both of which are larger under calibrations with lower values for ψ_s and ψ_u (i.e., higher Frisch elasticities). This result highlights a trade-off present in our simulations: higher Frisch elasticities contribute to substantially improve the results with respect to the autocorrelation of investment and the cross-correlation between output and investment, but at the same time decrease the fit between the model and the data with respect to the volatility of the unemployment rates, investment, and output.

TABLE 2.7: SENSITIVITY ANALYSIS FOR SIMULATIONS OF THE U.S. DATA, 1976:Q1–2016:Q4

	Standard deviation					Autocorrelation					Correlation with y				
	y	c	i	u_s	u_u	y	c	i	u_s	u_u	c	i	u_s	u_u	
Data	1.37	1.11	4.71	12.94	11.80	0.88	0.89	0.92	0.89	0.92	0.87	0.90	-0.80	-0.88	
Model, $\psi_s, \psi_u = 0.5$ and:															
$\theta = 0.95$	1.55	0.38	3.89	16.93	12.89	0.69	0.82	0.66	0.81	0.82	0.82	0.54	-0.86	-0.95	
$\theta = 0.85$	1.64	0.40	4.37	17.05	13.51	0.69	0.82	0.55	0.82	0.83	0.82	0.41	-0.86	-0.95	
$\theta = 0.75$	1.75	0.43	4.93	17.28	14.32	0.70	0.82	0.47	0.82	0.83	0.83	0.31	-0.85	-0.95	
Model, $\psi_s, \psi_u = 1$ and:															
$\theta = 0.95$	1.43	0.33	4.33	14.08	11.69	0.69	0.83	0.41	0.81	0.82	0.79	0.24	-0.86	-0.95	
$\theta = 0.85$	1.50	0.35	4.76	14.18	12.17	0.69	0.83	0.36	0.81	0.83	0.79	0.18	-0.85	-0.95	
$\theta = 0.75$	1.58	0.38	5.19	14.33	12.78	0.70	0.82	0.34	0.82	0.83	0.81	0.13	-0.84	-0.95	
Model, $\psi_s, \psi_u = 1.5$ and:															
$\theta = 0.95$	1.36	0.30	4.67	12.59	11.01	0.68	0.84	0.30	0.80	0.82	0.76	0.12	-0.85	-0.95	
$\theta = 0.85$	1.42	0.32	5.01	12.70	11.44	0.69	0.83	0.28	0.81	0.82	0.77	0.08	-0.84	-0.95	
$\theta = 0.75$	1.49	0.36	5.34	12.83	11.97	0.70	0.82	0.28	0.82	0.83	0.81	0.05	-0.83	-0.95	

Notes: Standard deviations are in percent. The row labelled “Data” refers to United States quarterly data for the period 1976:Q1–2016:Q4. The series for output (y), consumption (c) and investment (i) are from the *Bureau of Economic Analysis*. The series for the unemployment rates (u_s, u_u) are computed from monthly series of the *Current Population Survey*. The row labelled “Model” refers to results from 1000 model simulations of 164 quarters each, which is the same number of quarters as in the U.S. sample. The results are sample means of the statistics computed for each of the 1000 simulations. All variables are log-transformed and presented as deviations from a Hodrick-Prescott filtered trend with the smoothing parameter set to 1600.

2.6 Conclusion

In this paper we examine the business cycle volatility of the unemployment rates of high-skill and low-skill workers. We present evidence of an unemployment volatility gap in the United States and in thirteen E.U. countries from the late 1990s onwards, with the business cycle volatility of the unemployment rate being on average 37% larger for high-skill workers. Using U.S. data for the period 1976:Q1–2016:Q4, we also document a change in the volatility patterns of the unemployment rates of high-skill and low-skill workers. Up to the mid-1980s the business cycle volatility of the unemployment rate is slightly higher for low-skill workers, but from that point onwards the volatility of the unemployment rate becomes higher for high-skill workers, with the gap expanding substantially in the early 1990s.

We introduce a new framework to model unemployment into a business cycle model with worker heterogeneity, and we use it to examine the unemployment volatility differences observed in the data. In our model, each worker (high-skill or low-skill) offers a specific skill variety from which the households extracts monopolistic profits. Households bear the costs of searching for new jobs, but in equilibrium such costs are offset by the economic gains associated with expanding the number of skill varieties that are employed. On the firm side there is a variety effect that raises productivity when the labor input expands on the extensive margin. The intuition is that as the number of workers with differentiated skills increases, so does the scope for specialization gains. A calibration of the model matches key features of the volatility of the unemployment rates in the United States over the period 1976:Q1–2016:Q4. Specifically, the calibrated model: (i) yields unemployment rates that are more volatile for high-skill workers than for low-skill workers; (ii) approximates the standard deviations of the unemployment rates observed in the data; and (iii) yields unemployment rates that are substantially more volatile than output, replicating the relative volatility observed in the data.

Our study opens several lines of inquiry that can be addressed in future work. First, in the present paper we were unable to fully account for the volatility patterns of the U.S. unemployment rates for the 1976:Q1–1983:Q4 sub-period. However, our analysis is restricted to calibrations in which both θ and the Frisch elasticities are assumed to be the same for high-skill and low-skill workers, naturally imposing constraints on the ability of the model to fit the data. A natural next step is to investigate the effects of calibrating these parameters differently for high-skill workers and low-skill workers, and to examine whether such differences are compatible with empirical

evidence available in the literature.

Second, in the present paper we concentrate our analysis on the data from the United States, and we devote a great deal of attention to the shift in the volatility patterns of the unemployment rates from the pre-1984 sub-period to the post-1984 sub-period. However, we also document the presence of a volatility gap in the unemployment rates of high-skill and low-skill workers for thirteen E.U. countries. Future work could examine whether the cross-country differences in the size of the volatility gap can be explained within the framework we propose, and in particular it could assess to what extent such differences can be related to differences in θ , the parameter that governs the elasticity of substitution between workers of the same type.

Finally, future research could also examine three shortcomings observed in our results, namely: (i) the low volatility of consumption; (ii) the low autocorrelation of investment; and (iii) the low cross-correlation between output and investment. Two simple modifications of our model are worth considering. First, in our model we assume that households pool the income and consumption of high-skill and low-skill workers, and this may contribute to lower the volatility of consumption. In reality, there is evidence that couples sort according to schooling (see, e.g., Lewis and Oppenheimer, 2000; Chiappori et al., 2009), and therefore a more realistic model might consider high-skill households and low-skill households separately, each with their own income and consumption streams. Second, in our model we consider a law of motion for capital that does not account for capital adjustment costs. A natural extension of our work would be to examine whether including such costs improves the results with respect to the business cycle properties of investment, while at the same time retaining the results with respect to the volatility of the unemployment rates.

Appendix

In what follows, we drop the time subscript to denote the steady state values of the variables. To calibrate χ_s , χ_u , ϕ_s , and ϕ_u , in the steady state we: (i) normalize hours worked to one ($h_u = 1$, $h_s = 1$); (ii) take the average unemployment of unskilled workers as the target for u_u ; and (iii) take the average unemployment rate of the skilled workers as the target for u_s . Given that $u_u = \frac{q_u}{N^U}$ and $q_u = (N^u - n_u)$, targeting a value for u_u implies targeting a value for n_u as well, taking the size of the unskilled labor force N^U as given. Similarly, targeting a value for u_s implies

targeting a value for n_s as well, taking the size of the skilled labor force N^S as given. We use the fact that the ratio between n_s and n_u is constant in the steady state to write n_u and n_s as a function of the parameters of the model.

Let $\lambda = n_s/n_u$. Given that we normalize steady state hours to one, from (2.4) and (2.5) we can write:

$$\begin{aligned} l_u &= (n_u)^{\frac{1}{\theta}} \\ l_s &= \omega (\lambda n_u)^{\frac{1}{\theta}} \end{aligned}$$

and therefore from (2.3) we obtain the steady state value for the labor input l_t ,

$$l = \left(\omega \lambda^{\frac{1}{\theta}} \right)^v (n_u)^{\frac{1}{\theta}}. \quad (2.32)$$

Next we use (2.7) together with the production function (2.1) to define Γ as the steady state value of the ratio between k_t and l_t :

$$\Gamma \equiv \frac{k}{l} = \left(\frac{1}{\alpha} \left(\frac{1}{\beta} - 1 + \delta_k \right) \right)^{\frac{1}{\alpha-1}}, \quad (2.33)$$

which is simply a function of the parameters α , β and δ_k . We can use this result together with (2.32) to write the steady state capital as a function of n_u ,

$$k = \Gamma l = \Gamma \left(\omega \lambda^{\frac{1}{\theta}} \right)^v (n_u)^{\frac{1}{\theta}} \quad (2.34)$$

Finally, we use (2.32) and (2.34) to substitute into the production function in order to obtain the steady state output as a function of n_u :

$$y = \Gamma^\alpha \left(\omega \lambda^{\frac{1}{\theta}} \right)^v (n_u)^{\frac{1}{\theta}}. \quad (2.35)$$

Then, from the optimality condition (2.10) we obtain:

$$W_u = (1 - \alpha) (1 - v) \Gamma^\alpha \left(\omega \lambda^{\frac{1}{\theta}} \right)^v,$$

which, together with the symmetric equilibrium result (2.30), allows us to write w_u as a function of n_u :

$$w_u = (1 - \alpha) (1 - v) \Gamma^\alpha \left(\omega \lambda^{\frac{1}{\theta}} \right)^v (n_u)^{\frac{1-\theta}{\theta}}, \quad (2.36)$$

given that in the steady state $h_u = 1$. Plugging this result into the household's

optimality condition (2.25) we obtain:

$$\phi_u = (1 - \alpha) (1 - v) \Gamma^\alpha \left(\omega \lambda^{\frac{1}{\theta}} \right)^v (n_u)^{\frac{1-\theta}{\theta}} \frac{1 + \psi_u - \theta}{(1 - \beta - \beta \delta_u) (1 + \psi_u) (1 + \delta_u n_u)} \quad (2.37)$$

using the fact that in the steady state $g'_u(x_u) = \phi_u (1 + \delta_u n_u)$. Given the target for n_u and the calibration for the other parameters, expression (2.37) pins down the value of ϕ_u .

We can use a similar procedure to obtain the the expression used to pin down ϕ_s . We first use the replacement $n_u = \frac{n_s}{\lambda}$ in (2.4) and proceed as before to obtain the steady state output as a function of n_s , $y = \Gamma^\alpha \omega^v \lambda^{\frac{v-1}{\theta}} (n_s)^{\frac{1}{\theta}}$. Then, we substitute this result into the optimality condition (2.11) to obtain:

$$W_s = (1 - \alpha) v \Gamma^\alpha \omega^{v-1} \lambda^{\frac{v-1}{\theta}},$$

which, together with the symmetric equilibrium result allows us to write w_s as a function of n_s :

$$w_s = (1 - \alpha) v \Gamma^\alpha \omega^v \lambda^{\frac{v-1}{\theta}} n_s^{\frac{1-\theta}{\theta}} \quad (2.38)$$

given that in the steady state $h_s = 1$. Plugging this result into household's optimality condition (2.26) we obtain:

$$\phi_s = (1 - \alpha) v \Gamma^\alpha \omega^v \lambda^{\frac{v-1}{\theta}} (n_s)^{\frac{1-\theta}{\theta}} \frac{1 + \psi_s - \theta}{(1 - \beta + \beta \delta_s) (1 + \psi_s) (1 + \delta_s n_s)}$$

using the fact that in the steady state $g'_s(x_s) = \phi_s (1 + \delta_s n_s)$. Given the target for n_s and the calibration for the other parameters, expression (2.37) pins down the value of ϕ_s .

Given the steady state values for k , n_u , and n_s , we can compute the steady state values of y , i , g_u , and g_s to substitute into (2.18) in order to obtain the steady state value of consumption, c . We can then use expressions (2.23) and (2.36) to pin down the value of χ_u , and expressions (2.24) and (2.38) to pin down the value of χ_s .

Chapter 3

Countercyclical risk aversion in a two-country international business cycle model

3.1 Introduction

Attitudes toward risk change in response to economic conditions. People seem to be more risk averse when economic conditions are bad, and more risk tolerant when economic conditions are good. Along the economic cycle, risk aversion is low during expansion periods and high during contraction periods, making attitudes towards risk countercyclical. Evidence of this relationship has been found in macroeconomic and financial markets data. For example, Bollerslev et al. (2011) look at the volatility risk premium of the S&P500 market index as a proxy for risk aversion and study its variation over time. They find that the volatility risk premium responds to changes in several macroeconomic variables, and that it decreases when industrial production growth is strong, a result that is consistent with countercyclical risk aversion. Beber and Brandt (2006) show how market reactions to information about the state of the economy are consistent with the concept of countercyclical risk aversion. They look at how scheduled releases of U.S. macroeconomic information affect the preferences and beliefs of U.S. Treasury market participants. They show that the risk aversion implied in bond and option prices decreases in response to positive surprises in non-farm payroll, consumer price index, or unemployment information. In another study, Rosenberg and Engle (2002) use option data on the S&P500 market index to

compute risk aversion from an estimated time-varying empirical pricing kernel. They find that risk aversion significantly increases when credit spreads widen and when the slope of the yield curve flattens, two indicators of worsening economic conditions.

Studies at the aggregate level abstract from differences between market participants in terms of their actions, attitudes, and expectations about the economy. This makes it hard to establish exactly how risk aversion moves along the cycle at the individual level. But many studies that bypass this limitation by using microeconomic data indeed find that risk aversion is countercyclical. A recent article by Hoffmann et al. (2013) looks at the perceptions and actions of a set of Dutch investors during the 2008 financial crisis using matched survey and brokerage data. Investors were asked a series of qualitative questions designed to elicit their risk aversion, as well as their expectations for risk and return in the stock markets. The data reveal that investors's risk aversion increases when they experience poor stock market returns. Another study by Guiso et al. (2013) looks at how the crisis affected investors's risk aversion using data from a survey of customers of an Italian bank. They analyze two measures of risk aversion elicited once in 2007, before the crisis, and then again in 2009, and find a significant increase in both measures in 2009. They also find that the increase in risk aversion occurs both for those who had experienced losses, and those who did not. This suggests that people may change their attitudes towards risk even when they are not directly affected by changes in the surrounding economic conditions. In earlier work, Guiso and Paiella (2008) use data from a large Italian survey on household income and wealth to analyze how risk aversion relates to liquidity constraints and to exogenous background risk. They find that people become significantly more risk averse when exogenous background risk increases, and that this effect is more important than the effect of liquidity constraints.

Yet more evidence compatible with countercyclical risk aversion has been found in studies that rely on controlled experiments to measure individual risk aversion. In a recent study by Cohn et al. (2015), a set of financial professionals participated in an experiment in which they were primed to think about either a rising stock market or a declining stock market. Those primed with the rising stock market scenario subsequently made riskier choices in an investment task with real monetary payoffs, even though their expectations about the odds of success in the task did not differ from the expectations of those primed with the alternative scenario. In another study by Greenberg (2013), undergraduate students participated in an experiment in which they were asked to think they would become either wealthy or poor in the future. The students primed with the wealthy scenario subsequently selected risky

options more often in a series of lottery choice decisions that involved real monetary payoffs. The results of these studies suggest that fluctuations in risk aversion may be driven by a subconscious response to different economic contexts. A psychological mechanism of this kind is able to account for the findings of Guiso et al. (2013) that show that risk aversion may increase even for individuals who are not directly affected by adverse aggregate economic conditions.

In the macroeconomics literature the use of preferences that incorporate habit formation (e.g., Abel, 1990; Campbell and Cochrane, 1999) has been one way of introducing countercyclical risk aversion in the models. Under this type of preference specification risk aversion decreases when consumption goes above a certain reference level, as would happen during an economic expansion. When consumption drops below the reference level, risk aversion increases. But there are some limitations to the habit formation approach. One limitation is that risk aversion remains entangled with the elasticity of intertemporal substitution: when risk aversion increases the elasticity of intertemporal substitution decreases, and vice-versa. This makes it hard to distinguish whether along the economic cycle we are dealing with fluctuations in risk aversion or fluctuations in the elasticity of intertemporal substitution. Another limitation – in light of the studies by Cohn et al. (2015), Greenberg (2013), and Guiso et al. (2013) – is that in order for the individuals’s risk aversion to change there needs to be a material change in their own situation (i.e., their consumption must rise or fall relative to the habit). This mechanism is at odds with the finding that individuals may become more (or less) risk averse in response to changes in the surrounding economic context alone.

One convenient way to address these limitations is to work with the recursive preferences setup proposed by Kreps and Porteus (1978), Epstein and Zin (1989), and explored early on in the macroeconomics literature by Weil (1990). A central feature of this class of preferences is that there is one parameter to govern risk aversion and another parameter to govern the elasticity of intertemporal substitution, making the two independent. It is then possible to make the parameters dependent on an aggregate-level state variable, conceptually independent from the material situation of each individual. This approach has been explored, for example, by Melino and Yang (2003) in a closed economy setting to investigate if state-dependent risk aversion or state-dependent elasticity of intertemporal substitution can be used to address the equity premium puzzle (Mehra and Prescott, 1985) and the risk-free rate puzzle (Weil, 1989).

In this paper we contribute to the literature by using recursive preferences to introduce

countercyclical risk aversion in the standard two-country international business cycle model (see Backus et al., 1994). We follow an approach similar to that of Melino and Yang (2003) by making the risk aversion parameter state-dependent. More specifically, in our model the parameter that governs the households's risk aversion is driven by changes in aggregate output: risk aversion is lower when the economy expands, and higher when the economy contracts. This is in line with the aggregate-level findings of Bollerslev et al. (2011), and is compatible with the behavioral findings of Cohn et al. (2015) and Guiso et al. (2013). We take advantage of the separation between risk aversion and the elasticity of intertemporal substitution to keep the latter constant and isolate the effects of risk aversion fluctuations. Our goal is to understand to what extent countercyclical risk aversion can be used to address key mismatches that exist between the data and the standard two-country model.

The key intuition underlying our work relates to the standard exchange rate result obtained under complete markets:

$$\frac{q_{t+1}}{q_t} = \frac{m_{t,t+1}^*}{m_{t,t+1}}. \quad (3.1)$$

Expression (3.1) shows that the behavior of the exchange rate (q) is linked to the behavior of the stochastic discount factor in the home country ($m_{t,t+1}$) and in the foreign country ($m_{t,t+1}^*$). Because in our model households have recursive preferences, the stochastic discount factors on the right-hand side of equation (3.1) are twisted by an additional term not present in the standard case, one that depends on the continuation utility and its expected value, and also on the parameters that govern risk aversion and the elasticity of intertemporal substitution (Caldara et al., 2012). In this paper we exploit this feature of recursive preferences and complement it with countercyclical risk aversion to introduce an additional layer of variance in the dynamics of the exchange rate. To some extent, our work relates to other studies in the literature that exploit this feature to show that risk aversion plays a role in determining how well DSGE models can mimic asset price behavior. For example, Tallarini (2000) shows how increased risk aversion contributes to generate more realistic predictions for the risk-free bond rate and the market price of risk. More recently, Rudebusch and Swanson (2012) introduce recursive preferences into a standard DSGE model to study the long term premium on nominal bonds. They find that a high level of risk aversion helps the model generate a sizable term premium and a better fit to the empirical moments of bond yields.

We document how countercyclical risk aversion changes some of the predictions of

the standard two-country international business cycle model. We find that under reasonable assumptions for the volatility of the risk aversion parameter, our model significantly reduces the magnitude of the Backus and Smith (1993) puzzle. In the benchmark version of our model the correlation between the exchange rate and the consumption ratio is close to 0.5, well below the perfect correlation predicted by the standard two-country model with complete markets and non-recursive preferences. On the other hand, we find that countercyclical risk aversion only marginally increases the volatility of the exchange rate, which nevertheless remains ten times less volatile than in the data. Furthermore, we find that countercyclical risk aversion has little effect on the properties of the quantity variables, except for a small reduction in the cross-country correlation of consumption. However, this reduction does not significantly contribute to address the quantity anomaly (Backus et al., 1995): our model still generates a cross-country correlation of output that is much lower than the cross-country correlation of consumption, in contrast with what we observe in the data. We then examine whether the results hold under different assumptions about the behavior of risk aversion, and under a preference specification over the consumption-leisure bundle that is different from the Cobb-Douglas specification that underlies the standard two-country model.

Our work relates to recent studies that combine recursive preferences with some other mechanism to address different puzzles of the standard two country model. Colacito and Croce (2011) show that a model with recursive preferences and long-run risk can generate adequate volatility for the exchange rate, stochastic discount factors that are highly correlated across countries despite a low international correlation of consumption, and high cross-country correlation in asset returns even in the absence of a strong correlation in the fundamentals. A subsequent study (Colacito and Croce, 2013) shows how coupling a similar model with shifts in capital mobility helps to address the forward premium anomaly (Fama, 1984). The work by Gourio et al. (2013) looks at how introducing heterogenous country exposure to variable disaster-risks in a model with recursive preferences contributes to generate volatile exchange rates, address the Backus and Smith (1993) anomaly, and generate more realistic cross-country correlations of macroeconomic aggregates and asset returns. In another study, Benigno et al. (2011) show how the interaction between productivity shocks and monetary policy or target inflation shocks influences the behavior of the exchange rate in a model with recursive preferences, and how it can account for the negative coefficient in the uncovered interest rate parity regression. We add to this literature by establishing countercyclical risk aversion as another explanation for some of the puzzles of the two-country model.

The rest of the paper is organized as follows. In Section 3.2 we describe the benchmark version of our model, and in Section 3.3 we derive the corresponding equilibrium conditions. In Section 3.4 we calibrate the model and present the results of our numerical analysis. In Section 3.5 we conduct a sensitivity analysis and perform robustness checks with respect to assumptions regarding the households's utility function. We conclude with a discussion of the implications of our study in Section 3.6.

3.2 Model

Our international RBC model builds on Backus et al. (1994). The world economy is composed of two similar countries, Home and Foreign, each producing one intermediate good and one final good. Intermediate goods, which are used as inputs in the production of final goods, are imperfect substitutes and are traded internationally. Final goods, which are used by households for consumption or investment purposes, are used exclusively within the country that produces them. We move away from the standard two-country model in our treatment of the household sector: households have recursive preferences, and they exhibit countercyclical risk aversion that responds to the aggregate economic conditions in their own country. In what follows, for any generic variable x we use x_t to denote its value (at time t) in the Home country, and x_t^* to denote its value in the Foreign country. Unless otherwise necessary for clarity, we present model equations and equilibrium conditions for the Home country alone.

3.2.1 Households

The representative household of the Home country maximizes a recursive utility function of the form

$$V_t = \left((1 - \beta) U(c_t, l_t)^{1-\psi} + \beta E_t (V_{t+1}^{1-\gamma_t})^{\frac{1-\psi}{1-\gamma_t}} \right)^{\frac{1}{1-\psi}}. \quad (3.2)$$

Here V_t is the lifetime utility, $U(c_t, l_t)$ is the utility kernel, c_t is consumption, l_t is labor, and E_t is the mathematical expectation conditional on the information set available at time t . The parameter β is the rate of time preference, ψ is the inverse of the elasticity of intertemporal substitution, and γ_t measures the household's risk

aversion with respect to static gambles over V_{t+1} . In the benchmark version of the model we consider a Cobb–Douglas utility kernel:

$$U(c_t, l_t) = c_t^v (1 - l_t)^{1-v}, \quad (3.3)$$

where v is the share of consumption in utility.

Fluctuations in aggregate output drive the risk aversion parameter: when output expands, γ_t decreases; when output contracts, γ_t increases. In the benchmark version of the model the law of motion for γ_t is:

$$\gamma_t = \bar{\gamma} - \zeta \log \left(\frac{Y_{t-1}}{Y_{t-2}} \right), \quad (3.4)$$

where $\bar{\gamma}$ is the household’s baseline risk aversion, Y is the aggregate output of the Home country, and ζ is a parameter that measures how sensitive the household’s risk aversion is to changes in aggregate output, here used as a proxy for aggregate economic conditions. We assume $\zeta > 0$ to make risk aversion countercyclical. Equation (3.4) introduces, in a simple way, three important features in our countercyclical risk aversion mechanism. First, γ_t moves around a baseline level of risk aversion; this is to accommodate the notion that risk aversion has, in part, a stable component (Dohmen et al., 2011). Second, movements in γ_t are a response to changes in aggregate economic conditions; this is motivated by the findings of Cohn et al. (2015) and Guiso et al. (2013). Third, movements in γ_t are a lagged response to changes in aggregate economic conditions; this is line with recent findings by Kim (2014) about the relationship between risk aversion and the business cycle in the United States. Later on, in Section 3.5, we consider alternative formulations for the law of motion of γ_t and we check how they affect our results.

The household has access to complete financial markets where it can buy one-period state-contingent assets that pay one unit of consumption in the Home country. The household’s budget constraint is

$$c_t + i_t + E_t[r_{b,t+1}] b_{t+1} = w_t l_t + r_{k,t} k_t + b_t. \quad (3.5)$$

Here i_t is investment in physical capital; $r_{b,t+1}$ is the price, in period t , of an asset that pays one unit of Home country’s consumption in a particular state of period $t + 1$, divided by the probability of occurrence of that state given the information available at t ; b_{t+1} is the quantity of assets with maturity in period $t + 1$ purchased by the household in period t ; w_t is the wage rate; $r_{k,t}$ is the rental rate of capital;

and k_t is the household's capital stock in period t . The law of motion for capital is:

$$k_{t+1} = (1 - \delta) k_t + i_t, \quad (3.6)$$

where δ is the depreciation rate.

3.2.2 Production of intermediate goods

The representative producer of intermediate goods in the Home country combines capital and labor using standard Cobb–Douglas technology,

$$y_t = \exp(z_t) k_t^\alpha l_t^{1-\alpha}. \quad (3.7)$$

Here y_t is the output of intermediate goods, z_t measures total factor productivity, and α is the output elasticity with respect to capital. Aggregate output in the Home country is simply the sum of the output of all producers indexed by i over the continuum $[0, 1]$,

$$Y_t = \int_0^1 y_{i,t} di. \quad (3.8)$$

We model the behavior of total factor productivity following Backus et al. (1994): z_t and its foreign equivalent z_t^* follow a bivariate autoregressive process that has cross-country productivity spillovers and is described by

$$\begin{bmatrix} z_{t+1} \\ z_{t+1}^* \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} z_t \\ z_t^* \end{bmatrix} + \begin{bmatrix} \epsilon_{t+1} \\ \epsilon_{t+1}^* \end{bmatrix}. \quad (3.9)$$

Here a_{11} , a_{12} , a_{21} and a_{22} are positive constants, the term $\epsilon_{t+1} \sim N(0, \sigma_\epsilon^2)$ is the i.i.d. productivity shock of the Home country, and the term $\epsilon_{t+1}^* \sim N(0, \sigma_{\epsilon^*}^2)$ is the i.i.d. productivity shock of the Foreign country.

The representative producer of intermediate goods sells its output in a perfectly competitive market and earns profits given by:

$$\pi_{IG,t} = p_t y_t - w_t l_t - r_{k,t} k_t, \quad (3.10)$$

where p_t is the price of the intermediate good, w_t is the wage rate, and $r_{k,t} k_t$ is the rental rate of capital. The price p_t is denominated in units of the Home country's final good.

3.2.3 Production of final goods

The final good of the Home country is a composite of intermediate goods produced domestically and intermediate goods produced abroad. As in Backus et al. (1994), we use an Armington (1969) aggregator to describe the technology of the representative producer of final goods:

$$d_t = \left(\omega^{\frac{1}{\rho}} y_{h,t}^{\frac{\rho-1}{\rho}} + (1-\omega)^{\frac{1}{\rho}} y_{f,t}^{\frac{\rho-1}{\rho}} \right)^{\frac{\rho}{\rho-1}}, \quad (3.11)$$

where d_t is the output of final goods, $y_{h,t}$ is the input of domestic intermediate goods used by the Home country, $y_{f,t}$ is the input of foreign intermediate goods used by the Home country, ω measures the relative preference for domestic intermediate goods, and ρ is the elasticity of substitution between domestic and foreign intermediate goods.

The representative producer of final goods sells its output in a perfectly competitive market and earns profits given by:

$$\pi_{FG,t} = d_t - p_t y_{h,t} - q_t p_t^* y_{f,t}, \quad (3.12)$$

where p_t^* is the price of the foreign intermediate goods and q_t is the exchange rate. The price p_t^* is denominated in units of the Foreign country's final good, and the exchange rate is defined as the number of consumption units of the Home country that are exchangeable for one consumption unit of the Foreign country.

3.2.4 Trade and the exchange rate

The market for intermediate goods clears and the output of the producer of intermediate goods of the Home country is either used locally or exported to the Foreign country. In equilibrium we have:

$$y_t = y_{h,t} + y_{h,t}^*, \quad (3.13)$$

where $y_{h,t}$ is the quantity that is used in the Home country, and $y_{h,t}^*$ is the quantity that is exported to the Foreign country. In the same way, the output of the producer of intermediate goods of the Foreign country is either used locally or exported to the

Home country. In equilibrium we have

$$y_t^* = y_{f,t} + y_{f,t}^*. \quad (3.14)$$

where y_t^* is the output of the producer of intermediate goods of the Foreign country, $y_{f,t}$ is the quantity that is exported to the Home country, and $y_{f,t}$ is the quantity that is used locally in the Foreign country.

Under complete markets the exchange rate satisfies:

$$\frac{q_{t+1}}{q_t} = \frac{m_{t,t+1}^*}{m_{t,t+1}}, \quad (3.15)$$

where $m_{t,t+1}$ is the stochastic discount factor in the Home country, and $m_{t,t+1}^*$ is the stochastic discount factor in the Foreign country. In the Appendix we show that in the benchmark version of the model:

$$m_{t,t+1} = \beta \frac{c_t}{c_{t+1}} \left(\frac{U_{t+1}}{U_t} \right)^{1-\psi} \left(\frac{V_{t+1}^{1-\gamma_t}}{E_t(V_{t+1}^{1-\gamma_t})} \right)^{\frac{\psi-\gamma_t}{1-\gamma_t}}, \quad (3.16)$$

and by analogy in the Foreign country we have

$$m_{t,t+1}^* = \beta \frac{c_t^*}{c_{t+1}^*} \left(\frac{U_{t+1}^*}{U_t^*} \right)^{1-\psi} \left(\frac{V_{t+1}^{*1-\gamma_t^*}}{E_t(V_{t+1}^{*1-\gamma_t^*})} \right)^{\frac{\psi-\gamma_t^*}{1-\gamma_t^*}}. \quad (3.17)$$

We close the complete markets assumption following Benigno et al. (2011). We specify the initial holdings of the state-contingent assets so that their income, when converted to the proper unit, provides the same marginal utility across countries. Let g_t be the ratio of the marginal utilities of the asset income in the Home and Foreign countries,

$$g_t \equiv \frac{\frac{\partial V_t}{\partial c_t}}{\frac{\partial V_t^*}{\partial c_t^*} \frac{1}{q_t}} = \left(\frac{V_t}{V_t^*} \right)^\psi \left(\frac{U_t}{U_t^*} \right)^{1-\psi} \frac{c_t^*}{c_t} q_t. \quad (3.18)$$

We assume that in the initial period g_t is equal to one.

3.3 Equilibrium

The representative household chooses c_t , l_t , b_{t+1} , and k_{t+1} in order to maximize (3.2). The first order conditions with respect to consumption and labor are:

$$(1 - \beta) V_t^\psi U(c_t, l_t)^{-\psi} \frac{\partial U(c_t, l_t)}{\partial c_t} = \lambda_t, \quad (3.19)$$

$$(1 - \beta) V_t^\psi U(c_t, l_t)^{-\psi} \frac{\partial U(c_t, l_t)}{\partial l_t} = -\lambda_t w_t, \quad (3.20)$$

where λ_t is the usual Lagrange multiplier. Taking into account the utility kernel (3.3), we can combine equations (3.19) and (3.20) to obtain the consumption-leisure condition

$$\frac{1 - v}{v} \frac{c_t}{1 - l_t} = w_t. \quad (3.21)$$

The Euler equations for the asset holdings and for capital are given by,

$$m_{t,t+1} = r_{b,t+1}, \quad (3.22)$$

$$E_t [m_{t,t+1} (r_{k,t+1} + 1 - \delta)] = 1. \quad (3.23)$$

Equations (3.21) to (3.23), together with the stochastic discount factor (3.16), describe the optimal behavior of the representative household.

The representative producer of intermediate goods chooses the inputs k_t and l_t in order to maximize the profit described in equation (3.10), taking into account the market clearing price p_t . The first order conditions of the maximization problem are

$$p_t (1 - \alpha) y_t l_t^{-1} = w_t, \quad (3.24)$$

$$p_t \alpha y_t k_t^{-1} = r_{k,t}. \quad (3.25)$$

The representative producer of final goods chooses the combination $y_{h,t}$ and $y_{f,t}$ in order to maximize the profit described in equation (3.12). The first order conditions of the maximization problem are

$$y_{h,t} = p_t^{-\rho} \omega d_t, \quad (3.26)$$

$$y_{f,t} = (q_t p_t^*)^{-\rho} (1 - \omega) d_t. \quad (3.27)$$

Because the market for final goods is perfectly competitive, the representative

producer operates with zero profit. If we plug equations (3.26) and (3.27) into equation (3.12) and then impose a zero-profit condition, we obtain the following relationship between the prices of the intermediate goods

$$1 = \omega p_t^{1-\rho} + (1 - \omega) (q_t p_t^*)^{1-\rho}. \quad (3.28)$$

We can also relate the output of final goods with consumption, investment and net exports. Because the producer of final goods operates with zero profit and final goods are used locally for consumption or investment, we have

$$c_t + i_t = p_t y_{h,t} + q_t p_t^* y_{f,t}. \quad (3.29)$$

Then, we substitute the resource constraint (3.13) into equation (3.29) to obtain

$$y_t = \frac{(c_t + i_t)}{p_t} + \left(y_{h,t}^* - q_t \frac{p_t^*}{p} y_{f,t} \right). \quad (3.30)$$

The second term on the right hand side of equation (3.30) represents the net exports (nx), and we define $\tau \equiv q_t (p_t^*/p_t)$ as the terms of trade.

If we substitute the home and foreign stochastic discount factors into the exchange rate equation (3.15) and re-arrange terms, we obtain:

$$\frac{c_{t+1}^* q_{t+1}}{c_{t+1}} \left(\frac{U_{t+1}}{U_{t+1}^*} \right)^{1-\psi} = \frac{c_t^* q_t}{c_t} \left(\frac{U_t}{U_t^*} \right)^{1-\psi} \left(\frac{V_{t+1}^{*1-\gamma_t^*}}{E_t(V_{t+1}^{*1-\gamma_t^*})} \right)^{\frac{\psi-\gamma_t^*}{1-\gamma_t^*}} \left(\frac{V_{t+1}^{1-\gamma_t}}{E_t(V_{t+1}^{1-\gamma_t})} \right)^{\frac{\gamma_t-\psi}{1-\gamma_t}}, \quad (3.31)$$

which we can then re-write as:

$$g_{t+1} \left(\frac{V_{t+1}}{V_{t+1}^*} \right)^{-\psi} = g_t \left(\frac{V_t}{V_t^*} \right)^{-\psi} \left(\frac{V_{t+1}^{*1-\gamma_t^*}}{E_t(V_{t+1}^{*1-\gamma_t^*})} \right)^{\frac{\psi-\gamma_t^*}{1-\gamma_t^*}} \left(\frac{V_{t+1}^{1-\gamma_t}}{E_t(V_{t+1}^{1-\gamma_t})} \right)^{\frac{\gamma_t-\psi}{1-\gamma_t}} \quad (3.32)$$

to obtain the law of motion for the ratio of the marginal utilities of income in the Home and Foreign countries.

In the Appendix we show that the steady state values of capital and labor are:

$$k_{ss} = \frac{\Phi \Omega}{\Omega^\alpha - \delta \Omega + \Phi}, \quad (3.33)$$

$$l_{ss} = \frac{\Phi}{\Omega^\alpha - \delta \Omega + \Phi}, \quad (3.34)$$

where $\Omega = \left(\frac{1}{\alpha} \left(\frac{1}{\beta} + \delta - 1 \right) \right)^{\frac{1}{\alpha-1}}$ and $\Phi = \frac{v}{1-v} (1 - \alpha) \Omega^\alpha$. From the expressions (3.33) and (3.34) it is then straightforward to compute the steady state values of the remaining model variables.

3.4 Results

In this section we calibrate the benchmark version of the model and examine its statistical properties. In particular, we investigate whether the countercyclical risk aversion mechanism influences the behavior of the exchange rate and of the quantity variables. We solve our model using perturbation methods (see, e.g., Judd and Guu, 1992, 1997; Judd, 1996; Schmitt-Grohé and Uribe, 2004; Swanson et al., 2005), and we use a third-order approximation because of the role that risk aversion plays in our theoretical economy (see, e.g., Caldara et al., 2012).

3.4.1 Calibration

We calibrate the driving process for productivity following Backus et al. (1994). We assume that the standard deviation of the productivity shocks is the same in both countries, and that shocks are correlated across countries: $\sigma_\epsilon = \sigma_{\epsilon^*} = 0.00852$, $\text{Corr}(\epsilon, \epsilon^*) = 0.258$. For the matrix coefficients in the law of motion of productivity we have

$$\begin{bmatrix} z_{t+1} \\ z_{t+1}^* \end{bmatrix} = \begin{bmatrix} 0.906 & 0.088 \\ 0.088 & 0.906 \end{bmatrix} \begin{bmatrix} z_t \\ z_t^* \end{bmatrix} + \begin{bmatrix} \epsilon_{t+1} \\ \epsilon_{t+1}^* \end{bmatrix}. \quad (3.35)$$

In Table 3.1 we present the calibration for the remaining parameters of our model. For the parameters that relate to household utility, we follow the recent study by Gourio et al. (2013): we set the consumption share in utility to 0.34, the rate of time preference to 0.994, the baseline risk aversion to 8.5, and the elasticity of intertemporal substitution to 2, which implies $\psi = 0.5$. The calibration for the elasticity of intertemporal substitution exceeds the estimates obtained by Hall (1988), but it is nevertheless consistent with a series of studies that find the elasticity of intertemporal substitution to be in excess of 1 (see, e.g., Hansen and Singleton, 1982; Attanasio and Weber, 1989; Bansal and Yaron, 2004; Mulligan, 2004; Guvenen, 2006), as argued by Gourio et al. (2013). The value $\psi = 0.5$ is also in line with the calibration used by Colacito and Croce (2011).

TABLE 3.1: BASELINE PARAMETER CALIBRATION

	Symbol	Value
Rate of time preference	β	0.994
Elasticity of intertemporal substitution	$1/\psi$	2
Share of consumption in utility	v	0.34
Baseline risk aversion	$\bar{\gamma}$	8.5
Sensitivity of risk aversion to output fluctuations	ζ	170
Depreciation rate	δ	0.025
Capital share in the output of intermediate goods	α	0.36
Elasticity of substitution between intermediate goods	ρ	2.0
Relative preference for local intermediate goods	ω	0.85

Notes: The rate of time preference, the elasticity of intertemporal substitution, the share of consumption in utility, and the baseline level of risk aversion follow Gourio et al. (2013). The sensitivity of risk aversion to output fluctuations is set to make risk aversion movements consistent with Kim (2014). The depreciation rate, the capital share, the elasticity of substitution between intermediate goods, and the home bias follow Backus et al. (1994). See the text for details.

To calibrate ζ we rely on empirical evidence about the volatility of risk aversion. The source for our baseline calibration is the work by Kim (2014), who estimates the risk aversion parameter for the U.S. economy using the recursive preferences framework. The estimates from that study indicate that the standard deviation of risk aversion is between 25% and 30% of the mean value of risk aversion. We set $\zeta = 170$ in order to obtain a standard deviation for γ_t that is consistent with the lower bound of that interval.

For the parameters related to the production of final goods and the production of intermediate goods we take our calibration directly from Backus et al. (1994). We set the depreciation rate to 0.025, the capital share to 0.36, the elasticity of substitution between local and foreign intermediate goods to 1.5, and the relative preference for intermediate goods produced locally to 0.85.

3.4.2 Exchange rate

Table 3.2 presents key moments and correlations of the real exchange rate. We present two sets of model results: the column “Baseline ζ ” refers to the baseline calibration, and the column “Higher ζ ” refers to an alternative calibration in which risk aversion is twice as sensitive to output fluctuations ($\zeta = 340$). By comparing these two columns we get a better sense of how countercyclical risk aversion influences

the exchange rate statistics. The column “Data” presents, for each statistic, a corresponding range of empirical estimates obtained from the literature (Backus and Smith, 1993; Chari et al., 2002; Heathcote and Perri, 2002; Ravn and Mazzenga, 2004; Corsetti et al., 2008; Colacito and Croce, 2011; Thoenissen, 2011).¹

The baseline calibration generates insufficient volatility for the exchange rate: the standard deviation of the exchange rate is about one-fifth of the standard deviation of output, but in the data this ratio is clearly greater than two. This finding holds even with our alternative calibration, which generates only a marginal increase in the relative volatility of the exchange rate. These results show that the benchmark version of our model cannot easily account for the exchange rate volatility we observe in the data, regardless of how much risk aversion moves in response to output fluctuations. The model, however, does a reasonable job of matching the persistency of the exchange rate. With the baseline calibration the first-order autocorrelation of the exchange rate is 0.85, close to the upper bound of the empirical range. With the alternative calibration the autocorrelation falls further in line with the data, but here too the difference is very small relative to the results from the baseline calibration.

The benchmark version of the model does not generate reasonable correlations between the exchange rate and both output and the net exports ratio. For output the baseline calibration yields a correlation with the exchange rate that is around three and a half times larger than the upper bound of the empirical range; for the net exports ratio the baseline calibration yields a negative correlation with the exchange rate, but in the data the correlation is positive. Under the alternative calibration the results move closer to the data, suggesting that countercyclical risk aversion helps to mitigate these problems, but the simulated correlations remain far from their corresponding empirical ranges.

One important result of the model relates to the correlation between the exchange rate and relative consumption. In the data this correlation is often close to zero or negative, but theoretical models with complete markets usually produce a correlation that is equal or close to one. This mismatch is referred to as the Backus and Smith (1993) puzzle or the consumption-real exchange rate anomaly (Chari et al., 2002). We see that with the baseline calibration our model produces a correlation between the exchange rate and relative consumption that is well below one, and with the alternative calibration the correlation is even lower. These results suggest that the

¹A detailed list of references for each of the empirical ranges that appear in the tables is available upon request.

TABLE 3.2: EXCHANGE RATE STATISTICS

Variable	Data	Model	
		Baseline ζ	Higher ζ
<i>Real exchange rate</i>			
Standard deviation relative to output	[2.23, 4.36]	0.205	0.227
Autocorrelation	[0.80, 0.83]	0.850	0.821
<i>Correlations with the real exchange rate</i>			
Output	[0.07, 0.13]	0.445	0.403
Net exports	[0.14, 0.14]	-0.373	-0.248
Relative consumption	[−0.71, 0.15]	0.564	0.211

Note: With exception of the net exports ratio, statistics refer to logged and HP-filtered variables, with $\lambda = 1600$ (see Hodrick and Prescott, 1997). Model variables are q for the real exchange rate, y for output, nx/y for the ratio of net exports to output, and c/c^* for relative consumption. Model results are computed by simulating the theoretical economy for 10,000 periods starting from the deterministic steady state, and then discarding the first 1000 periods as a burn-in. The column labeled “Data” presents a range of empirical estimates obtained from existing literature. See the text for details.

countercyclical risk aversion mechanism embodied in our model can significantly decrease the magnitude of the consumption-real exchange rate anomaly.

3.4.3 Quantities

Table 3.3 presents key moments and correlations of the quantity variables. As before, the column “Baseline ζ ” refers to the results of the baseline calibration, the column “Higher ζ ” refers to the results of the alternative calibration in which risk aversion is twice as sensitive to output fluctuations, and the column “Data” presents a corresponding range of empirical estimates obtained from the literature (Backus et al., 1995; Stockman and Tesar, 1995; Chari et al., 2002; Ambler et al., 2004; Ravn and Mazzenga, 2004; Dmitriev and Roberts, 2012; Gourio et al., 2013).

The baseline calibration does a reasonable job of replicating the volatility of investment, employment, and of the net exports ratio relative to the volatility of output. In the model, investment is about three and a half times more volatile than output, a value that is close to the upper bound of the empirical range. Employment and the net exports ratio are both less volatile than output, and the correlations in the model fall well within the empirical range. The baseline calibration, however, does not

TABLE 3.3: BUSINESS CYCLE STATISTICS

Variable	Data	Model	
		Baseline ζ	Higher ζ
<i>Standard deviations relative to output</i>			
Consumption	[0.63, 0.95]	0.310	0.316
Investment	[2.78, 3.46]	3.498	3.499
Employment	[0.26, 0.86]	0.546	0.547
Net exports	[0.11, 0.69]	0.217	0.227
<i>Correlations with output</i>			
Consumption	[0.69, 0.88]	0.679	0.661
Investment	[0.74, 0.94]	0.949	0.948
Employment	[0.48, 0.88]	0.960	0.959
Net exports	[−0.41, −0.27]	−0.610	−0.596
<i>Cross-country correlations</i>			
Output	[0.28, 0.64]	0.153	0.152
Consumption	[0.15, 0.53]	0.783	0.714
Investment	[0.22, 0.61]	−0.367	−0.368
Employment	[0.20, 0.42]	−0.238	−0.245

Notes: With exception of the net exports ratio, statistics refer to logged and HP-filtered variables, with $\lambda = 1600$ (see Hodrick and Prescott, 1997). Model variables are y for output, c for consumption, i for investment, l for employment, and nx/y for the ratio of net exports to output. Model results are computed by simulating the theoretical economy for 10,000 periods starting from the deterministic steady state, and then discarding the first 1000 periods as a burn-in. The column labeled “Data” presents a range of empirical estimates obtained from existing literature. See the text for details.

generate sufficient volatility for consumption; in fact, with respect to this statistic the benchmark version of our model does worse than the standard two-country model. The results from the alternative calibration show these patterns hold even when risk aversion is more sensitive to output fluctuations, indicating that countercyclical risk aversion has little impact on the relative volatility of the quantity variables. This finding is consistent with the results of previous studies that use recursive preferences and find the volatility of the quantity variables to be largely unaffected by the level of risk aversion (see, e.g., Tallarini, 2000; Rudebusch and Swanson, 2012).

In terms of co-movement between output and the other quantity variables, the benchmark model delivers mixed results. With the baseline calibration the correlation between output and consumption is close to the lower bound of the empirical range, and the correlation between output and investment is close to the upper bound of the empirical range. For the net exports ratio, however, the model yields a correlation with output that is significantly more negative than in the data. The alternative calibration generates virtually the same results, indicating that the countercyclical risk aversion mechanism does little to affect the co-movement of the quantity variables within each country.

Turning to the international co-movement of the quantity variables, we see that our benchmark model shares some of the shortcomings of the standard two-country model of Backus et al. (1994). With the baseline calibration, output is less correlated across countries than in the data, and consumption is more correlated across countries than in the data; more important, in the model the cross-country correlation of consumption is higher than that of output, but in the data we observe the opposite. Our benchmark model then suffers from what is commonly referred to as the quantity anomaly (Backus et al., 1995). Furthermore, our benchmark model generates negative cross-country correlations for investment and employment, but in the data those correlations are positive. The results from the alternative calibration are similar to those of the baseline calibration, but we observe a non-trivial decrease in the cross-country correlation of consumption.

3.4.4 The role of the elasticity of intertemporal substitution

With recursive preferences the parameters that govern risk aversion and the elasticity of intertemporal substitution jointly determine the household's attitude towards resolution of uncertainty. Under the specification used in equation (3.2), when $\gamma_t > \psi$

the household has a preference for early resolution of uncertainty, and when $\gamma_t < \psi$ the household has a preference for late resolution of uncertainty. In our model γ_t varies over time but ψ remains fixed, and the importance of a fluctuation in γ_t is influenced, to some extent, by the size of ψ . Therefore, it is important to ask whether the results of the previous sections hold when we consider a different value for ψ . In this section we examine the behavior of the benchmark model when we set $\psi = 2$, implying that the elasticity of intertemporal substitution is 0.5; this value is commonly used in the literature (see, e.g., Caldara et al., 2012; Rudebusch and Swanson, 2012) and compatible with the estimates obtained by Vissing-Jorgensen (2002).

In Table 3.4 we present the same moments and correlations of Tables 3.2 and 3.3, now computed using the new calibration for ψ , both for the case with baseline sensitivity on the risk aversion parameter ($\zeta = 170$), and for the case with higher sensitivity on the risk aversion parameter ($\zeta = 340$). Overall the benchmark model yields the same exchange rate statistics as before: (i) the standard deviation of the exchange rate is still about one-fifth of the standard deviation of output; (ii) the autocorrelation of the exchange rate remains close to the upper bound of the empirical range; and (iii) the correlations between the exchange rate and both output and the net exports ratio still fail to conform with the data. Furthermore, the model behaves as before when we increase the sensitivity of risk aversion to output fluctuations. We observe an increase in the relative volatility of the exchange rate and a decrease in its autocorrelation, but both movements are very small in magnitude. We also observe non-negligible decreases in the correlations between the exchange rate and output and the net exports ratio, but the model still generates a correlation between the exchange rate and output that is too high, and a correlation between the exchange rate and the net exports ratio that is counterfactually negative.

There is, however, one important difference in the exchange rate statistics obtained under $\psi = 2$. For the case of baseline sensitivity in the risk aversion parameter, the correlation between the exchange rate and relative consumption (0.78) is significantly higher than the correlation observed under the $\psi = 0.5$ (0.56). Despite this difference, the effects of the countercyclical risk aversion are still present: the correlation between the exchange rate and relative consumption continues to exhibit a large decrease (from 0.78 to 0.49) when we let the γ_t be twice as sensitive to output fluctuations. Furthermore, the drop in the correlation is about the same size as the drop in the correlation observed under $\psi = 0.5$. The results provide two important insights about how countercyclical risk aversion relates to the Backus and Smith (1993)

puzzle in our model. First, the precise value of ψ does not seem to matter for how much the puzzle can be reduced by the countercyclical risk aversion mechanism. Second, the elasticity of intertemporal substitution is slightly less important than countercyclical risk aversion in shaping the correlation between the exchange rate and relative consumption. Changing ψ from 0.5 to 2 increases the correlation by 0.22, while doubling ζ decreases it by 0.3 or more.

Under the new calibration for the elasticity of intertemporal substitution there are some differences in the results that relate to the quantity variables, but in general the effects of countercyclical risk aversion are similar to those we observe under the baseline calibration. Relative to output, consumption is now more volatile, and investment and employment are now less volatile, but the volatility of these variables is still unrelated to how strongly countercyclical risk aversion is. For the net exports ratio, the simulated statistics are virtually the same as before. Turning to the correlations between output and the other quantity variables, we see that results are the same as before except for consumption, which is now significantly more correlated with output in the baseline ζ case. Moreover, the correlation between output and consumption is now much more sensitive to the volatility of the risk aversion parameter: doubling the sensitivity of γ_t to output fluctuations now decreases the correlation by 0.23, whereas the baseline calibration for the elasticity of intertemporal substitution the decrease was almost non-existent. When households are more reluctant to shift consumption across periods, consumption moves more in line with output, but the behavior of risk aversion becomes more important in determining the path of consumption.

The cross-country correlations are somewhat different with the new elasticity of intertemporal substitution, but how they relate countercyclical risk aversion is not changed in any fundamental way. For output, the cross-country correlation is the same as before and is still insensitive to how much the household's risk aversion moves in response to output fluctuations. For investment and employment, the correlations become more negative than under the baseline calibration of ψ , but they too are still insensitive to how much volatile the household's risk aversion is. The cross-country correlation of consumption is now somewhat higher than before, but still decreases when the household's risk aversion is more sensitive to output fluctuations. We do observe, however, that the cross-correlation of consumption is now less sensitive to how strongly countercyclical risk aversion is. Under the baseline calibration for the elasticity of intertemporal substitution, if risk aversion becomes twice as sensitive to output fluctuations the correlation drops by 0.07, whereas with

the new calibration for the elasticity of intertemporal substitution the drop is under 0.03.

Taken together, the results we have presented in this section show that the effects of countercyclical risk aversion observed in our benchmark model hold regardless of whether the elasticity of intertemporal substitution is high or low. Because the risk aversion parameter and the elasticity of intertemporal substitution are the two core parameters of the recursive preferences, the results provide a first indication that our findings are not a spurious byproduct of a specific combination of parameter values, but instead a robust feature of a model with recursive preferences and countercyclical risk aversion.

3.4.5 The role of the response lag of risk aversion

An important aspect of the countercyclical risk aversion mechanism described in section 3.2 is the lag with which the households's risk aversion moves in response to fluctuations in output. For simplicity, in the benchmark model we have assumed that risk aversion movements are determined by the growth rate of output observed in the preceding period. However, it is important to verify if the results of the benchmark model hold when we consider a different lag structure and allow the risk aversion parameter to move in response to more distant output fluctuations. In this section we generalize the law of motion of γ_t to accommodate different timings in the response of risk aversion to fluctuations in output,

$$\gamma_t = \bar{\gamma} - \zeta \log \left(\frac{Y_{t-j}}{Y_{t-j-1}} \right). \quad (3.36)$$

While there are no obvious constraints on how high j can be, we concentrate our analysis on a limited set of values. We turn to the empirical evidence provided by Kim (2014) about the correlation between risk aversion and the U.S. business cycle to determine the range of values of k we should consider in our analysis. Kim (2014) reports estimates of the correlation between risk aversion, γ_t , and the (lagged) monthly U.S. unemployment rate, U_{t-j} , for different values of j . The estimated correlations increase with j , being highest at the 12-month lag and then gradually decreasing for longer lags, with the correlations reported for 18 and 24 months being at least 85% as large as the correlation reported for 12 months. Taking this evidence into account, here we study the behavior of our model with lags up eight quarters ($j = 8$) in equation (3.36).

TABLE 3.4: THE ROLE OF THE ELASTICITY OF INTERTEMPORAL
SUBSTITUTION

Variable	Baseline EIS		EIS = 0.5	
	Baseline ζ	Higher ζ	Baseline ζ	Higher ζ
<i>Real exchange rate</i>				
Standard deviation relative to output	0.205	0.227	0.211	0.232
Autocorrelation	0.850	0.821	0.849	0.823
<i>Correlations with the real exchange rate</i>				
Output	0.445	0.403	0.448	0.408
Net exports	-0.373	-0.248	-0.362	-0.247
Relative consumption	0.564	0.211	0.783	0.493
<i>Standard deviations relative to output</i>				
Consumption	0.310	0.316	0.485	0.490
Investment	3.498	3.499	2.947	2.950
Employment	0.546	0.547	0.395	0.395
Net exports	0.217	0.227	0.215	0.224
<i>Correlations with output</i>				
Consumption	0.679	0.661	0.898	0.661
Investment	0.949	0.948	0.934	0.948
Employment	0.960	0.959	0.940	0.959
Net exports	-0.610	-0.596	-0.606	-0.596
<i>Cross-country correlations</i>				
Output	0.153	0.152	0.151	0.151
Consumption	0.783	0.714	0.833	0.805
Investment	-0.367	-0.368	-0.488	-0.489
Employment	-0.238	-0.245	-0.466	-0.473

Notes: With exception of the net exports ratio, statistics refer to logged and HP-filtered variables, with $\lambda = 1600$ (see Hodrick and Prescott, 1997). Model variables are y for output, c for consumption, i for investment, l for employment, and nx/y for the ratio of net exports to output. Model results are computed by simulating the theoretical economy for 10,000 periods starting from the deterministic steady state, and then discarding the first 1000 periods as a burn-in. The column labeled “Data” presents a range of empirical estimates obtained from existing literature. See the text for details.

In Table 3.5 we present key moments and correlations obtained by simulating the benchmark model for different values of j . In all simulations we use the baseline calibration described in Table 3.1. We see that, overall, the results of the benchmark model do not change with the value of j being used in the simulation. There are some differences across simulations in terms of the correlation between the exchange rate and output, and in terms of the correlation between the exchange rate and the net exports ratio, but the differences are small and do not exhibit any meaningful pattern. The stability of the results suggests that the findings discussed in Sections 3.4.2 and 3.4.3 are not dependent on a particular lag structure for the law of motion of risk aversion. In particular, we confirm that, regardless of the value of j , the benchmark model: (i) is unable to generate sufficient volatility in the exchange rate; (ii) decreases the magnitude of the Backus and Smith (1993) puzzle; and (iii) does not eliminate the quantity anomaly.

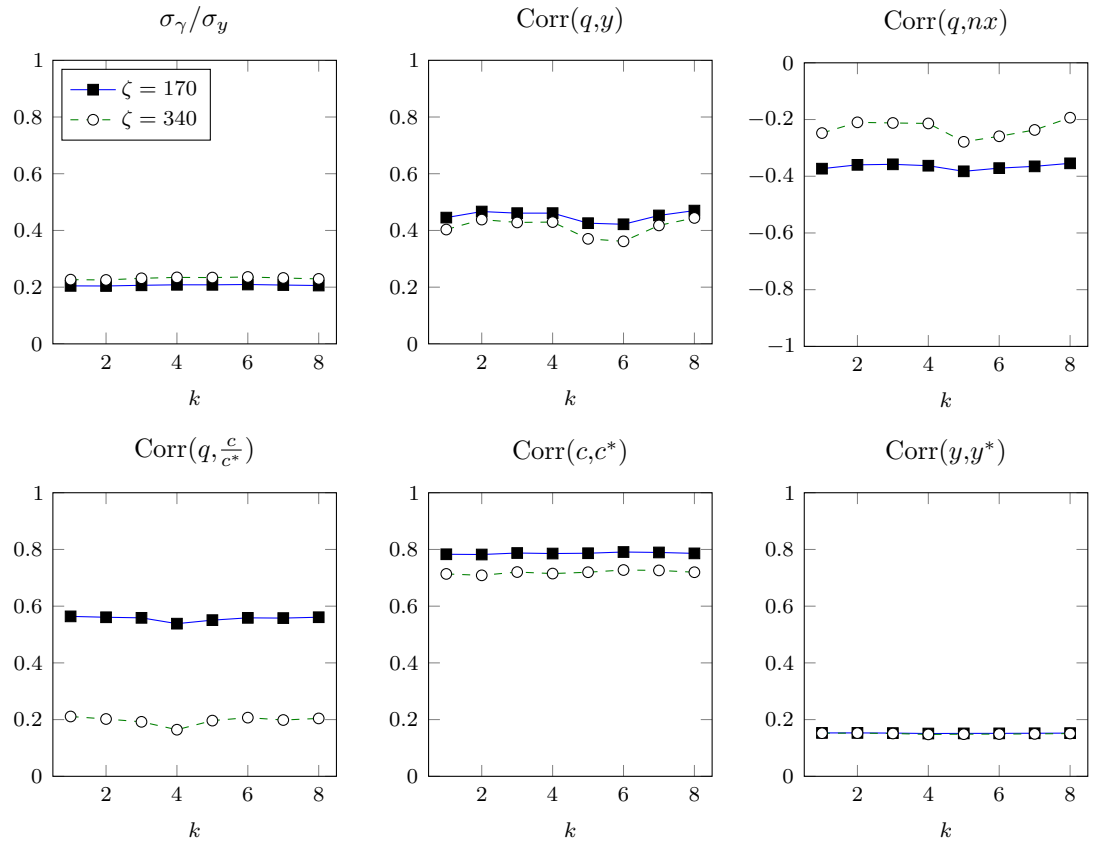
In Figure 3.1 we provide further evidence that our key findings do not stem from a particular lag structure for the law of motion of risk aversion. Each panel plots the value of a simulated statistic for different values of j under two calibrations: the solid line refers to the baseline calibration described in Table 3.1; the dashed line refers to an alternative calibration in which risk aversion is twice as sensitive to fluctuations in output ($\zeta = 340$). The leftmost top panel presents the relative volatility of the exchange rate, and we see that regardless of the value of j , the countercyclical risk aversion mechanism has little influence over this statistic. The other two top panels present correlations between the exchange rate and output and the net exports ratio. Although these correlations change slightly with the value of j , we see that the way they relate to countercyclical risk aversion is independent of j . The bottom panels of Figure 3.1 show that the contribution of countercyclical risk aversion to address the Backus and Smith (1993) puzzle and the quantity anomaly (Backus et al., 1995) is not dependent on a particular lag structure for equation (3.36). In the leftmost panel we see that the correlation between the exchange rate and the consumption ratio drops, regardless of the value of j . In the two rightmost panels we confirm that countercyclical risk aversion does not help significantly in addressing the quantity anomaly: when risk aversion becomes more strongly countercyclical, the cross-country correlation in consumption decreases only slightly, and the cross-country correlation in output exhibits no significant change.

TABLE 3.5: THE ROLE OF THE RISK AVERSION RESPONSE LAG

Variable	Risk aversion response lag				
	$k = 1$	$k = 2$	$k = 3$	$k = 4$	$k = 8$
<i>Real exchange rate</i>					
Standard deviation relative to output	0.205	0.204	0.207	0.208	0.206
Autocorrelation	0.850	0.850	0.852	0.857	0.854
<i>Correlations with the real exchange rate</i>					
Output	0.445	0.467	0.461	0.461	0.470
Net exports	-0.373	-0.360	-0.358	-0.363	-0.354
Relative consumption	0.564	0.561	0.559	0.538	0.561
<i>Standard deviations relative to output</i>					
Consumption	0.310	0.312	0.309	0.314	0.314
Investment	3.498	3.494	3.495	3.494	3.493
Employment	0.546	0.548	0.547	0.549	0.549
Net exports	0.217	0.204	0.212	0.204	0.200
<i>Correlations with output</i>					
Consumption	0.679	0.682	0.679	0.676	0.681
Investment	0.949	0.950	0.949	0.950	0.950
Employment	0.960	0.960	0.960	0.959	0.959
Net exports	-0.610	-0.597	-0.599	-0.601	-0.594
<i>Cross-country correlations</i>					
Output	0.153	0.153	0.152	0.151	0.152
Consumption	0.783	0.782	0.787	0.786	0.786
Investment	-0.367	-0.367	-0.367	-0.368	-0.368
Employment	-0.238	-0.239	-0.240	-0.243	-0.240

Notes: With exception of the net exports ratio, statistics refer to logged and HP-filtered variables, with $\lambda = 1600$ (see Hodrick and Prescott, 1997). Model variables are y for output, c for consumption, i for investment, l for employment, and nx/y for the ratio of net exports to output. Model results are computed by simulating the theoretical economy for 10,000 periods starting from the deterministic steady state, and then discarding the first 1000 periods as a burn-in. The column labeled “Data” presents a range empirical estimates obtained from existing literature. See text for details.

FIGURE 3.1: EFFECTS OF COUNTERCYCLICAL RISK AVERSION UNDER DIFFERENT RESPONSE LAGS



3.5 Robustness

In this section we investigate whether the effects of countercyclical risk aversion documented in Section 3.4 hold when we modify key assumptions about the behavior of the representative household. More specifically, we analyze how the model performs when we consider alternative specifications for the behavior of the risk aversion parameter, γ_t , and for the utility kernel, $U(c_t, l_t)$.

3.5.1 Asymmetric response of risk aversion

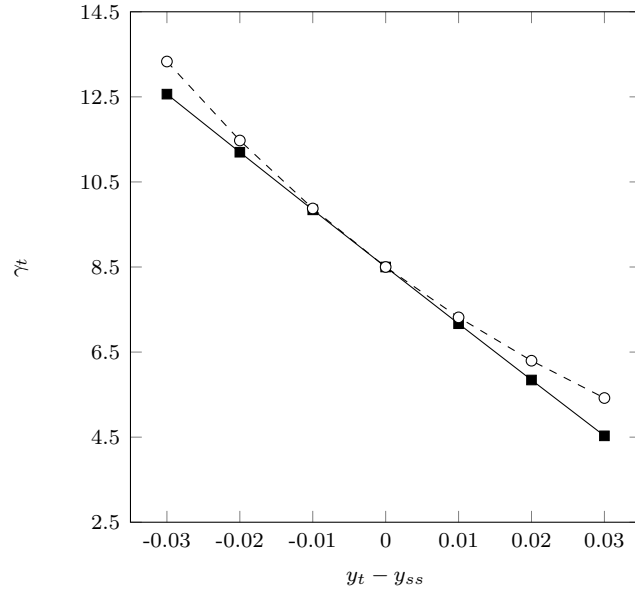
One important feature of the benchmark model is that, for reasonable range of output fluctuations, downturns and expansions have almost symmetric effects on risk aversion: the increase in γ_t caused by a given drop in output is roughly equal, in absolute terms, to the decrease in γ_t caused by an expansion in output of the same magnitude. This straightforward assumption implies that the effects of bad economic conditions are as large, but in the opposite direction, as the effects of good economic conditions. We now move away from the specification laid out in equation (3.4) and instead assume that the law of motion of γ_t is:

$$\gamma_t = \bar{\gamma} \exp^{-\zeta(y_{t-1} - y_{t-2})}, \quad (3.37)$$

where we set $\zeta = 15$ as the baseline value to deliver a volatility of γ_t that is comparable with the volatility obtained with the benchmark model (using equation 3.4 and the baseline calibration presented in Table 3.1).

The difference between the two specifications is apparent in Figure 3.2, which depicts how risk aversion behaves in response to movements in output, here computed around the steady state. The solid line shows the quasi-linear relationship between movements in output and movements in risk aversion implied by the benchmark version of the model. The dashed line shows the response of risk aversion under the specification laid out in equation (3.37): the increase in γ_t during a contraction is larger, in absolute terms, than the decrease in γ_t for an equally sized expansion. This kind of asymmetric response of γ_t implies that households are more sensitive to bad economic conditions than to good economic conditions. Evidence that individuals react differently to bad outcomes and good outcomes of similar size has been documented by, e.g., Kahneman and Tversky (1979).

FIGURE 3.2: RISK AVERSION MOVEMENTS – BENCHMARK MODEL VS. ASYMMETRIC RESPONSE



In Table 3.6, under “Asymmetric response of γ_t ”, we present key moments and correlations obtained by simulating the model with the new law of motion for γ_t . To carry out a thorough comparison with the results of the benchmark model, we present results for $\zeta = 15$ (column “Low ζ ”), which delivers a volatility of γ_t similar to that of the baseline case in Section 3.4, but also the results obtained when we double the sensitivity of γ_t to fluctuations in output by setting $\zeta = 30$ (column “High ζ ”), thereby mirroring the analysis in Section 4. We see that the results closely match those obtained with the benchmark version of the model. The different response of γ_t to downturns and expansions does not significantly change the relative volatility of the exchange rate, which is still ten times smaller than in the data and relatively insensitive to how strongly countercyclical γ_t is. Similarly, the volatility of the quantity variables (relative to output) is also largely unaffected by how much γ_t moves in response to output fluctuations, and the simulated statistics show no systematic deviation from the ones yielded by the benchmark model.

We observe two small differences in the correlation between the exchange rate and the consumption ratio. First, for the same level of volatility in γ_t , the benchmark model presents a smaller correlation than the one obtained under the asymmetric response implied by equation (3.37). Second, the correlation is more sensitive to how strongly countercyclical risk aversion is in the benchmark model: starting from the baseline, doubling the sensitivity of γ_t to fluctuations in output decreases the correlation between the exchange rate and the consumption ratio by 0.35, but only

by 0.3 under the asymmetric behavior of γ_t . Nevertheless, the countercyclical risk aversion embedded in our continues to play an important role in reducing the size of the Backus and Smith (1993) puzzle.

3.5.2 GHH utility kernel

The benchmark version of our model uses a Cobb–Douglas utility kernel, but as pointed out by Guvenen (2009) that implies that ψ and v simultaneously set the elasticity of intertemporal substitution, the amount of time the household devotes to work, and the Frisch elasticity of labor supply. In this section we investigate whether the results of our model hold when we move away from the Cobb–Douglas utility kernel. More specifically, we follow Guvenen (2009) and adapt the utility kernel U_t to the specification proposed by Greenwood et al. (1988):

$$U(c_t, l_t) = \left(c_t - \varphi \frac{l_t^{1+\chi}}{1+\chi} \right), \quad (3.38)$$

where in line with Greenwood et al. (1988) we set $\chi = 0.6$, implying a Frisch elasticity of labor supply close to 1.7, and we set φ so that the representative household devotes one third of its time to work in the steady state. The new specification for the utility kernel implies some changes to the equilibrium conditions and the steady state.²

In Table 3.6, under “GHH kernel”, we present key moments and correlations obtained by simulating the model using the GHH utility kernel, and the original law of motion for γ_t described in equation (3.4). Again, for a thorough comparison with the results of the benchmark model we present results for the two levels of sensitivity of γ_t to fluctuations in output studied in Section 3.4: $\zeta = 150$ as in the baseline calibration of Table 3.1 (column “Low ζ ”), and $\zeta = 300$ for the case in which risk aversion is twice as sensitive to output fluctuations (column “High ζ ”). Predictably, the change in the utility kernel causes some significant changes in the results. Relative to output, the exchange rate and investment become less volatile, and consumption and employment become more volatile. Nevertheless, the effects of countercyclical risk aversion are, in general, very similar to those observed under a Cobb–Douglas utility kernel. The relative volatility of the exchange rate raises only modestly when risk aversion is more strongly countercyclical, and the relative volatility of all quantity variables is largely unrelated to how large the fluctuations in γ_t are. Like in the benchmark model, the correlation between the exchange rate and the consumption ratio is

²Detailed derivations are available upon request.

TABLE 3.6: ALTERNATIVE SPECIFICATIONS

Variable	Data	Asymmetric response of γ_t		GHH kernel	
		Low ζ	High ζ	Low ζ	High ζ
<i>Standard deviations relative to output</i>					
Exchange rate	[2.23, 4.36]	0.204	0.221	0.137	0.180
Consumption	[0.63, 0.95]	0.310	0.315	0.555	0.576
Investment	[2.78, 3.46]	3.498	3.499	2.572	2.576
Employment	[0.26, 0.86]	0.546	0.546	0.621	0.622
Net exports	[0.11, 0.69]	0.217	0.225	0.217	0.239
<i>Correlations with the real exchange rate</i>					
Output	[0.07, 0.13]	0.447	0.409	0.242	0.128
Net exports	[0.14, 0.14]	-0.378	-0.273	-0.205	0.067
Relative consumption	[-0.71, 0.15]	0.581	0.278	0.479	0.117
<i>Cross-country correlations</i>					
Output	[0.28, 0.64]	0.153	0.152	0.368	0.367
Consumption	[0.15, 0.53]	0.786	0.729	0.240	0.181

Notes: With exception of the net exports ratio, statistics refer to logged and HP-filtered variables, with $\lambda = 1600$ (see Hodrick and Prescott, 1997). Model variables are y for output, c for consumption, i for investment, l for employment, and nx/y for the ratio of net exports to output. Model results are computed by simulating the theoretical economy for 10,000 periods starting from the deterministic steady state, and then discarding the first 1000 periods as a burn-in. The column labeled “Data” presents a range empirical estimates obtained from existing literature. See text for details.

well below 1 and very sensitive to how strongly countercyclical γ_t is. Furthermore, fluctuations in risk aversion are still irrelevant to the cross-country correlation in output, but do play a role in shaping the cross-country correlation of consumption, which becomes lower when γ_t is more volatile. However, the results suggest that introducing GHH preferences help the model address the quantity anomaly, as the cross-country correlation is now larger for output than for consumption.

There are, however, meaningful differences in the correlations between the exchange rate and output, and between the exchange rate and net exports. Although the effects of countercyclical risk aversion are essentially the same as in the benchmark model, under the GHH utility kernel they become much more pronounced: the correlation between the exchange rate and output is cut in half when γ_t becomes twice as volatile, whereas in the benchmark model the reduction is much more subdued; and the correlation between the exchange rate and the net exports ratio now moves much more closer to the empirical range when risk aversion becomes more volatile.

3.6 Conclusion

In this paper we used recursive preferences together with an endogenous risk aversion parameter to introduce countercyclical risk aversion into an otherwise standard two-country RBC model. With recursive preferences the behavior of the exchange rate directly depends on the risk aversion of the Home and Foreign countries, and thus is sensitive to how risk aversion moves along the business cycle. In our model we assume that risk aversion increases when aggregate output decreases, and vice versa. This setup builds an additional source of fluctuations into the dynamics of the exchange rate, and modifies certain results of the standard two-country model. Under reasonable assumptions for the volatility of the risk aversion parameter, we find that this setup is still unable to generate sufficient volatility for the exchange rate, but it successfully reduces the magnitude of Backus and Smith (1993) puzzle: the correlation between movements in the exchange rate and in the consumption ratio is well below 1, and is highly sensitive to how strongly countercyclical risk aversion is.

Our robustness checks indicate that the main results hold with different specifications for the law of motion of the risk aversion parameter and for the period utility of the households. The relatively small increase in the volatility of the exchange rate and the significant reduction in the Backus and Smith (1993) puzzle are still present if

we: (i) change the lag with which risk aversion reacts to fluctuations in output; (ii) assume that increases in risk aversion during contractions are larger than decreases in risk aversion during expansions; and (iii) move away from the Cobb-Douglas utility and instead consider an utility kernel based on Greenwood et al. (1988).

Appendix

Derivation of the SDF

In equilibrium, the utility of a fractional unit of consumption in period $t + 1$ must be the same as the utility of that same that fractional unit of consumption in period t , when properly discounted by the stochastic discount factor $m_{t,t+1}$:

$$\frac{\partial V_t}{\partial c_t} m_{t,t+1} \xi = \frac{\partial V_t}{\partial c_{t+1}} \xi, \quad (3.39)$$

for ξ arbitrarily close to zero. We can apply the chain rule to the derivative on the right hand side of (3.39) to obtain

$$\frac{\partial V_t}{\partial c_t} m_{t,t+1} = \frac{\partial V_t}{\partial V_{t+1}} \frac{\partial V_{t+1}}{\partial c_{t+1}}. \quad (3.40)$$

First we differentiate V_t with respect to c_t to obtain

$$\frac{\partial V_t}{\partial c_t} = V_t^\psi (1 - \beta) U_t^{1-\psi} c_t^{-1} v. \quad (3.41)$$

Then we iterate this result forward one period:

$$\frac{\partial V_{t+1}}{\partial c_{t+1}} = V_{t+1}^\psi (1 - \beta) U_{t+1}^{1-\psi} c_{t+1}^{-1} v, \quad (3.42)$$

and finally we compute

$$\frac{\partial V_t}{\partial V_{t+1}} = V_t^\psi \beta E_t \left(V_{t+1}^{1-\gamma_t} \right)^{\frac{\gamma_t - \psi}{1 - \gamma_t}} V_{t+1}^{-\gamma_t}. \quad (3.43)$$

If we substitute equations (3.41), (3.42), and (3.43) into equation (3.39) and re-arrange terms, we obtain the stochastic discount factor for the Home country,

$$m_{t,t+1} = \beta \frac{c_t}{c_{t+1}} \left(\frac{U_{t+1}}{U_t} \right)^{1-\psi} \left(\frac{V_{t+1}^{1-\gamma_t}}{E_t (V_{t+1}^{1-\gamma_t})} \right)^{\frac{\psi - \gamma_t}{1 - \gamma_t}}. \quad (3.44)$$

Steady state

Let x_{ss} denote the steady state value of the variable x_t . In the steady state the bond holdings of the representative household are zero, and investment replaces the depreciated capital, $i_{ss} = \delta k_{ss}$. From the budget constraint of the representative household, we obtain

$$c_{ss} + \delta k_{ss} = w_{ss} l_{ss} + r_{k,ss} k_{ss}. \quad (3.45)$$

In the steady state, capital and labor are paid according to their respective marginal productivities. We differentiate (3.7) with respect to k_t and l_t to obtain the expressions for the marginal productivity of capital and labor,

$$\frac{\partial y_t}{\partial k_t} = \alpha \exp^{z_t} k_t^{\alpha-1} l_t^{1-\alpha},$$

$$\frac{\partial y_t}{\partial l_t} = (1 - \alpha) \exp^{z_t} k_t^\alpha l_t^{-\alpha}.$$

The wage rate and the rental rate of capital in the steady state are then

$$w_{ss} = (1 - \alpha) k_{ss}^\alpha l_{ss}^{1-\alpha} \equiv \left. \frac{\partial y_t}{\partial l_t} \right|_{X_t = X_{ss}}, \quad (3.46)$$

$$r_{k,ss} = \alpha k_{ss}^{\alpha-1} l_{ss}^{1-\alpha} \equiv \left. \frac{\partial y_t}{\partial k_t} \right|_{X_t = X_{ss}}, \quad (3.47)$$

where X_t is a vector containing all model variables, and X_{ss} is a vector containing the steady state values for X_t .³ since in the steady state $z_{ss} = 0$. Substituting (3.46) and (3.47) into (3.45) and re-arranging terms yields.

$$c_{ss} + \delta k_{ss} = k_{ss}^\alpha l_{ss}^{1-\alpha}. \quad (3.48)$$

Next, we use the Euler equation for capital to establish that in the steady state

$$\frac{k_{ss}}{l_{ss}} = \left(\frac{1}{\alpha} \left(\frac{1}{\beta} + \delta - 1 \right) \right)^{\frac{1}{\alpha-1}} \equiv \Omega. \quad (3.49)$$

Substituting this result into (3.48), re-arranging terms, and applying some algebraic manipulation yields

$$c_{ss} = l_{ss} (\Omega^\alpha - \delta \Omega). \quad (3.50)$$

³Recall that in the steady state $z_{ss} = 0$, and thus: (i) $w_{ss} = (1 - \alpha) \exp^{z_{ss}} k_{ss}^\alpha l_{ss}^{1-\alpha} = (1 - \alpha) k_{ss}^\alpha l_{ss}^{1-\alpha}$; (ii)

Note that the results (3.49) and (3.50) are independent from the preferences of the representative household over the consumption-leisure bundle.

From the F.O.C. with respect to consumption and labor for the maximization problem of the representative household, as described by equations (3.19) and (3.20), we establish that in the steady state

$$\frac{v}{1-v} w_{ss} = \frac{c_{ss}}{1-l_{ss}}.$$

Using this result together with (3.46) and (3.49) yields

$$\frac{c_{ss}}{1-l_{ss}} = \frac{v}{1-v} (1-\alpha) \Omega^\alpha \equiv \Phi,$$

which can be re-stated as

$$c_{ss} = (1-l_{ss}) \Phi.$$

Substituting into (3.50) this result and re-arranging terms yields

$$l_{ss} = \frac{\Phi}{\Omega^\alpha - \delta\Omega + \Phi}. \quad (3.51)$$

Finally, we substitute (3.51) into (3.49) to obtain

$$k_{ss} = \frac{\Phi\Omega}{\Omega^\alpha - \delta\Omega + \Phi}. \quad (3.52)$$

From (3.51) and (3.52) it is straightforward to compute the steady state values for the remaining variables.

Chapter 4

Expectations and risk attitudes: Evidence from a longitudinal survey in Tshwane, South Africa

4.1 Introduction

Attitudes towards risk are considerably different across individuals, and economists and psychologists have devoted a substantial amount of research to understanding the origins of this heterogeneity. The interest stems from the important role that risk and risk-taking play in everyday life. Individuals routinely make choices in contexts that involve a trade-off between safer and riskier options, and the choices they make have consequences – for themselves, and sometimes for markets or society by virtue of the aggregation of individual actions.

Several studies examine the importance of sociodemographic characteristics in explaining differences in risk attitudes. The evidence presented by Dohmen et al. (2010) and Dohmen et al. (2011) indicates that characteristics such as age, gender, marital status, education and cognitive ability significantly predict the willingness to take risks (see also Byrnes et al. (1999) and Croson and Gneezy (2009) for meta-analyses of the role of gender, and Harbaugh et al. (2002) for further evidence on the role of age). Other studies emphasize how differences in risk attitudes may be partially explained by genetic factors (see, e.g., Cesarini et al., 2009; Kuhnen and Chiao, 2009).

A different strand of the literature investigates how the exposure to certain events influences risk attitudes. One set of studies examines how risk attitudes react to natural and man-made disasters such as earthquakes, tsunamis, volcano eruptions, floods or radioactive contamination (see, e.g., Eckel et al., 2009; Cassar et al., 2011; Willinger et al., 2013; Page et al., 2014; Cameron and Shah, 2015; Goebel et al., 2015; Hanaoka et al., 2015). These studies commonly find that risk preferences change for individuals who are exposed to such disasters. Similarly, other studies show that exposure to conflict-related violence can also lead to changes in risk attitudes (see, e.g., Voors et al., 2012; Callen et al., 2014; Kim and Lee, 2014). A different set of studies examines how risk attitudes are influenced by macroeconomic shocks and the macroeconomic environment to which individuals are exposed. Malmendier and Nagel (2011) find that households who experience low stock market returns exhibit a lower willingness to take financial risks. Guiso et al. (2013) analyze repeated observations of a sample of Italian bank customers and conclude that they became more risk averse after the 2008 financial crisis.

In this paper, we use data from a longitudinal survey conducted in the Tshwane Municipality, South Africa, to investigate the relationship between risk attitudes and expectations about the future. Expectations, much like actual experiences, evoke emotions such as excitement, fear, or anxiety. Studies in the field of neuroscience show that two brain areas that process risk – the nucleus accumbens and the anterior insula (Preuschoff et al., 2006) – are also associated with the processing of emotions: positive emotions activate the nucleus accumbens (see, e.g., Bjork et al., 2004), and negative emotions activate the anterior insula (see, e.g. Chua et al., 1999; Simmons et al., 2004, 2006). The activation of these areas has been shown to modify risk attitudes and predict behavior in controlled experiments (see, e.g., Kuhnen and Knutson, 2005), and more recently Kuhnen and Knutson (2011) have suggested that two specific emotions – excitement and anxiety – influence the risk attitudes of individuals. Furthermore, some studies have shown that cortisol, a stress-related hormone, can modulate risk attitudes both in a laboratory setting (see, e.g., Kandasamy et al., 2014) and in the field (see, e.g., Coates and Herbert, 2008). Thus, by evoking emotional states that activate specific brain areas or trigger hormonal responses, expectations may indeed be an important determinant of risk attitudes.

We concentrate on two different types of expectations. First, we examine the role of expectations that individuals have about the economic environment of their communities. This is relevant because people in our sample face a paucity of wage work, and they often resort to running small (sometime informal) businesses to earn

their income. If, for example, worse economic expectations reduce the willingness to take risks, this can accentuate the negative effects of an economic slowdown: not only the anticipation of negative economic conditions reduces the attractiveness and availability of business opportunities, but at the same time individuals also become less willing to take on the risks associated with existing business opportunities. Second, we examine the role of expectations that individuals have about their own health. This is relevant because people in our sample face a large variance in disease prevalence, including HIV, with varying current and future consequences. If, for example, better health expectations increase the willingness to take risks, policies that improve the health conditions and health expectations of individuals may also have ramifications for everyday decisions that individuals make in contexts where risk is an important factor.

We find that economic expectations significantly predict the willingness to take risks. According to our estimates, an increase in economic expectations by an amount equal to its average within-respondent standard deviation is associated with an increase in the willingness to take risks of about 4% of its average within-respondent standard deviation. In our data almost two-thirds of our respondents exhibit shifts in their economic expectations, and for about 20% of the respondents our estimates would imply shifts in the willingness to take risks that are as large as 25% of its average within-respondent standard deviation. We also find some evidence that health expectations significantly predict the willingness to take risks, with better health expectations being associated with a higher willingness to take risks. An increase in health expectations by an amount equal to its average within-respondent standard deviation is associated with an increase in the willingness to take risks of about 3% of its average within-respondent standard deviation. However, while the results relating to economic expectations hold under a variety of robustness checks, the results regarding health expectations do not.

Our estimations control for a set of sociodemographic characteristics of the respondents such as age, education, marital status, education, wealth, life satisfaction, many of which have been shown to predict risk attitudes. In some cases we successfully replicate the findings of previous studies. For example, we find a higher willingness to take risks among those who are married or living together with their spouses, and among those who report a higher life satisfaction, in line with the results of Dohmen et al. (2011). We find a quadratic relationship between age and risk attitudes, with the estimates implying that the willingness to take risks is increasing with with age for those younger than 64 years, and decreasing with with age for those older

than 64 years. In contrast with other studies, in our sample the educational level, health conditions, or wealth of the respondents does not significantly predict their willingness to take risks.

Because a large proportion of respondents in our sample reports owning a business, we also examine whether the relationship between economic expectations and the willingness to take risks is different for business owners and non-owners. There are two reasons that lead us to consider such possibility. First, business owners may have more complete information about the economic environment of their communities, and this may make their economics expectations systematically different from the expectations of non-owners. Second, business owners may also be intrinsically different with respect to their willingness to take risks, as higher risk tolerance has been found to be positively related with entrepreneurial activity (see, e.g., Van Praag and Cramer, 2001; Cramer et al., 2002; Hartog et al., 2002; Ekelund et al., 2005; Kan and Tsai, 2006; Caliendo et al., 2009). Our results, however, provide no evidence of a statistically significant difference between business owners and non-owners in terms of the relationship between economic expectations and the willingness to take risks. This conclusion holds in a specification in which the dummy variable that indicates the business owner status is interacted with only the expectations term, and also in a specification in which the business owner dummy is fully interacted with the remaining covariates.

We contribute to the literature in three ways. First, we expand the body of evidence related to the determinants of risk attitudes. Our results indicate that economic expectations are a significant predictor of the willingness to take risks, and they suggest the possibility that health expectations may also play a role in determining risk attitudes. Our results also provide further evidence that age, marital status and life satisfaction significantly predict risk attitudes. Second, our results are also relevant to the debate about the stability of risk attitudes over time. A series of recent studies has suggested that risk preferences may have a time-varying component (Guiso and Paiella, 2008; Malmendier and Nagel, 2011; Cohn et al., 2015), and our results on the relationship between economic expectations and the willingness to take risks suggest a possible explanation for its presence. According to our findings, shifts in economic expectations are associated with shifts in risk attitudes. As economies experience the short-term fluctuations associated with the business cycle, the economic expectations of individuals are naturally subject to changes, and this causes risk attitudes to fluctuate over time. Finally, the results of our study are also relevant for policymakers because they highlight how decision making under risk may

be affected by policies that shift people’s expectations. We provide some examples that are directly relevant for the respondents in our sample, and also discuss potential implications for our understanding of asset price bubbles, conditional on the external validity of our study.

The rest of the paper is organized as follows. In Section 4.2 we describe the empirical framework and data used in the study. In Section 4.3 we present the results of our main statistical analysis, and we perform a robustness analysis in Section 4.4. In Section 4.5 we discuss our results and their policy implications, as well as the limitations of our study. We close with some concluding remarks in Section 4.6.

4.2 Method

4.2.1 Sample

Our study uses a sample of 2680 individuals who were interviewed as part of a three-wave longitudinal survey conducted in the Tshwane Municipality, South Africa, between 2009 and 2014. Respondents were selected from predominantly African areas according to the sampling procedure described in Chao et al. (2012). The first wave of the survey consisted of a census of the enumeration areas selected for sampling, and respondents answered a short questionnaire that elicited information about their sociodemographic characteristics, health status, business activities, and the composition of their households. The second and third waves of the study revisited the respondents interviewed during the first wave, this time with a more comprehensive questionnaire. The extended questionnaire included additional questions about the sociodemographic and psychological characteristics of the respondents, their health status, their attitudes and beliefs about health risks and HIV stigma, and more details of their business activities. In all waves we asked respondents a set of questions related to their risk attitudes and economic and health expectations.

4.2.2 Dependent variables

The main dependent variable in our study is a 5-point scale of risk attitudes. More specifically, we asked respondents to rate their willingness to take risks using the following question:

“Are you generally a person who is fully prepared to take risks, or do you generally always try to avoid taking risks?”

1–Do everything to avoid risks;

5–Fully prepared to take risks”.

This question is similar to a question used by Dohmen et al. (2011) to elicit general risk attitudes, except theirs is an 11-point scale. In the second and third waves of our study, we also asked respondents to rate their willingness to take risks using an 11-point version of the question presented above. We use this additional data to perform robustness checks of our main results, and to provide some comparability between our study and other studies that use the 11-point scale to examine risk attitudes.

4.2.3 Main independent variables

The main independent variables in our study are two 5-point measures of economic and health expectations. We asked respondents about their expectations for the economic environment of their communities using the following question:

“What do you think the overall economic environment in your community will be like in one year from today? Do you think the overall economic environment will:

1–Decline a lot;

2–Decline a little;

3–Remain the same;

4–Improve a little;

5–Improve a lot.”

We then asked respondents about their expectations for their own health by asking:

“Please think realistically before answering this question. Do you think your health next year will be:

1–Much worse than today;

2–Worse than today;

3–Same as today;

4–Better than today;

5–Much better than today.”

It is important to contrast the scope of our measures of expectations with the scope of our measures of risk attitudes. Our questions about expectations relate to two specific domains: the economic environment of our respondents’ communities, and our respondents’ own health. On the other hand, our questions about risk attitudes refer to the willingness to take risks *in general*, not in terms of economic risks or health risks in particular. The availability of data dictates this difference, as the survey administered to our respondents did not include questions about the willingness to take economic risks or health risks in particular. Because our aim is to investigate the effects of expectations on the willingness to take risks, it is important to consider the potential implications of this difference in the scope of the variables.

Let us first consider a hypothetical scenario in which risk attitudes in different domains reflect mostly an individual’s core risk attitudes – there is a correlation between measures of risk attitudes across different domains, and also between measures of risk attitudes in general and measures of domain-specific risk attitudes. Recent work by Dohmen et al. (2011) and Einav et al. (2012) presents evidence consistent with this scenario. How would this affect our ability to examine the potential relationship between expectations and risk attitudes? Suppose that expectations pertaining to a specific domain influence risk attitudes *only* in that same domain. For example, economic expectations influence the willingness to take economic risks, but not the willingness to take other types of risks. For this to be possible, the effect of economic expectations on the willingness to take economic risks would need to operate without affecting the individual’s core risk attitudes, and economic expectations would not influence measures of risk attitudes in general. In this case, it is unlikely that we would detect such an effect with the data available for our study.

Now suppose instead that expectations pertaining to a specific domain influence risk attitudes in other domains as well. For example, suppose that economic expectations influence the willingness to take economic risks, health risks, and other types of risks. A plausible situation would be for economic expectations to influence an individual's core risk attitudes, and this would then influence risk attitudes in other domains.¹ In this case economic expectations would influence measures of risk attitudes in general, and we might be able to detect such an effect with the data available for our study.

Let us now consider an alternative scenario in which risk attitudes are mostly domain-specific and a common core of risk attitudes is absent – there is little to no correlation between measures of risk attitudes across different domains, and also between measures of risk attitudes in general and measures of domain-specific risk attitudes. Barseghyan et al. (2011) present evidence consistent with this scenario. Expectations pertaining to a specific domain may influence risk attitudes in that domain, but are unlikely to influence risk attitudes in other domains (otherwise risk attitudes across domains would be correlated), and also unlikely to affect measures of risk attitudes in general. In this case, we might not be able to detect such an effect with the data available for our study.

4.2.4 Other independent variables

Our study includes a set of additional variables that relate to the respondents' sociodemographic characteristics. Age has been shown to be a significant predictor of risk attitudes (see, e.g., Pålsson, 1996; Halek and Eisenhauer, 2001; Dohmen et al., 2011), and in our regressions we control for the age of the respondent with a linear and a quadratic term. We also control for the current physical and mental health of the respondents using two measures derived from the SF-12 health instrument (Ware et al., 1995). The health measures allow us to address two potential sources of bias in our estimations. First, those with poor physical health may have a different willingness to take risks (see, e.g., Dohmen et al., 2011), and they may also have different expectations about their health in the future. Second, those in poor mental health may form expectations that are systematically different from the expectations of respondents in good mental health, and at the same time they might also report a systematically different willingness to take risks.

¹An alternative in which core risk attitudes remain unchanged and all the effect operates strictly on the non-shared portion of the variance of several unrelated domain-specific risk attitudes seems unlikely.

We control for education using a categorical variable that classifies our respondents into those who: (i) have some primary education or less; (ii) completed primary education; (iii) have some secondary education; (iv) completed secondary education, and; (v) have at least some tertiary education. Education can be a confounding variable in two ways. First, better educated people may hold systematically different expectations about the future economic conditions in their community or about their own health, and at the same time they may be intrinsically different in their willingness to take risks. In the literature the evidence on the relationship between education and risk attitudes is mixed, as some studies have found education to be positively related with higher risk tolerance (see, e.g., Miyata, 2002; Hryshko et al., 2011) and others have found education to be negatively related with higher risk tolerance (see, e.g., Tanaka et al., 2010). Second, higher levels of education have been found to be associated with better health outcomes and lower risk of health problems (see Cutler and Lleras-Muney (2008) for a comprehensive review of available evidence), and the health expectations of better educated individuals may also be systematically different from the expectations of those with less education.

We also control for the respondent's wealth as evidence available from some studies indicates that risk aversion is negatively related to wealth (see, e.g., Halek and Eisenhauer, 2001; Guiso and Paiella, 2008). We construct a wealth index based on whether the respondent's household has access to a set of eight items: a cell phone, a computer, a landline telephone, a microwave, a radio, a refrigerator, a television, and a washing machine. For each item we create a dummy variable that takes the value 1 if the respondent's household has access to that item, and the value 0 otherwise. We then perform a principal component analysis with the dummy variables and take the first principal component as our wealth index.

We also include variables for marital status and life satisfaction, both of which have been shown to predict risk attitudes. Marital status is a dummy variable that indicates if the respondent is married or living together. Life satisfaction is measured on a scale from 0 to 100, with 0 indicating that the respondent is completely dissatisfied with her life, and 100 indicating that the respondent is completely satisfied with her life.

4.2.5 Model and estimation framework

We estimate a linear relationship between an individual's willingness to take risks, $WTR_{i,t}$, and his expectations about the economic environment of his community,

$E_{i,t}[Y_{t+1}]$, and about his own health, $E_{i,t}[H_{i,t+1}]$:

$$WTR_{i,t} = \beta_0 + \beta_1 E_{i,t}[Y_{t+1}] + \beta_2 E_{i,t}[H_{i,t+1}] + \delta X_{i,t} + \nu_i + \varepsilon_{i,t}. \quad (4.1)$$

Here δ is a vector of coefficients associated with the vector $X_{i,t}$ of additional covariates, ν_i is an individual-specific fixed effect, and $\varepsilon_{i,t}$ is an error term. In the context of our study, accommodating the presence of individual-specific fixed effects is important because non-observable traits may simultaneously affect the willingness to take risks and the expectations variables. Consider, for example, someone who is intrinsically optimistic. This individual might downplay the negative consequences of risky choices and therefore report a higher willingness to take risks. At the same time, this individual may have a more rosy view of the future that translates into more positive expectations. The use of fixed effects estimation allows us to tackle this issue and deal with potential omitted variable bias problems.

4.3 Results

4.3.1 Summary statistics

Table 1 presents summary statistics for the willingness to take risks, economic and health expectations, and other explanatory variables used in our study. Our panel is unbalanced, with almost all of the 2680 respondents having data in the first wave, but about 38% of them not being present in at least one of the subsequent waves.²

On average, the respondents in our sample are slightly over 40 years old, around 40% of them have completed at least secondary education, and almost half of them are married or living together with their spouses. The average physical health of our respondents, as measured by the SF12 instrument, remains essentially the same across the three waves of the survey, but the average mental health exhibits a small (statistically non-significant) increase over time. Around one third of the respondents reports owning a business, which in many cases is operated by the business owner alone. A small fraction of the respondents relocates within the enumeration areas

²The difference in the number of observations across waves is caused by survey attrition and non-response to the questions used in this study. For about 20% of the respondents in our sample we have data in the first two waves, but not in the third wave. For about 14% of the respondents we have data in the first and third waves, but not in the second wave. For about 4% of the respondents we only have data in the first wave.

TABLE 4.1: SUMMARY STATISTICS FOR THE WILLINGNESS TO TAKE RISKS,
ECONOMIC AND HEALTH EXPECTATIONS, AND SOCIODEMOGRAPHIC
CHARACTERISTICS

	Wave 1		Wave 2		Wave 3	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Willingness to take risks						
5-point scale	2.98	1.64	3.25	1.51	3.53	1.51
11-point scale	-	-	5.65	3.74	6.34	3.73
Economic expectations	3.81	0.93	3.45	1.03	3.44	1.14
Health expectations	3.84	0.86	3.81	0.88	3.68	0.86
Age	41.37	14.99	42.78	14.35	44.79	14.70
Education						
Less than primary schooling	0.18	0.39	0.15	0.36	0.16	0.36
Primary schooling completed	0.06	0.23	0.05	0.22	0.06	0.23
Some secondary schooling	0.37	0.48	0.37	0.48	0.36	0.48
Secondary schooling completed	0.25	0.43	0.25	0.43	0.25	0.43
Above secondary schooling	0.14	0.35	0.18	0.38	0.17	0.38
Married or cohabiting	0.44	0.50	0.46	0.50	0.47	0.50
Business owner	0.35	0.48	0.36	0.48	0.33	0.47
Physical health	50.00	9.23	50.71	8.45	52.59	7.61
Mental health	46.40	10.00	49.42	10.69	51.32	9.44
Wealth index	0.00	1.50	0.00	1.52	0.00	1.53
Life satisfaction	60.79	26.19	53.80	25.82	58.93	26.40
Relocated	-	-	0.05	0.21	0.07	0.25
Male	0.40	0.49	0.40	0.49	0.39	0.49
Observations	2632		2191		2034	

Notes: The table reports weighted means and standard deviations.

covered by our survey. About 5% of those interviewed during the second wave had moved since our first interview, and about 7% of those interviewed during the third wave had moved since we last interviewed them. These relocation rates do not include respondents who have moved to places outside our enumeration areas, and who we did not interview in the second and third waves.

The mean of the willingness to take risks measured on a 5-point scale ranges from 2.98 in the first wave to 3.53 in the third wave, but the respondents in our sample cannot be generically described as having relatively neutral attitudes toward risk. Although across all waves 20% of our respondents rate their willingness to take risks as a 3 on the 5-point scale, 58% use one of the two extremes of the scale to describe their attitudes towards risk (i.e., they chose either “1–*Do everything possible to avoid all risks*” or “5–*Fully prepared to take risks*” as their answer to the risk attitudes question).

Our respondents have mostly positive expectations about the economic environment in their communities and about their own health. The mean of the economic expectations measured on a 5-point scale ranges from 3.44 in the third wave to 3.81 in the first wave, with 58% of the respondents (across all waves) expecting an improvement in the economic environment of their community, and 28% expecting the economic environment to remain the same. In terms of health expectations our respondents are equally optimistic: 63% expect their health to improve, and less than 6% expect their health to deteriorate. As a result, the mean health expectations measured on a 5-point scale ranges from 3.68 in the third wave to 3.84 in the first wave.

Table 4.2 presents the mean willingness to take risks conditional on the economic expectations of the respondent. In general, respondents who have better economic expectations are more willing to take risks, with the Spearman rank correlation between the two variables being 0.078 in the first wave, 0.167 in the second wave, and 0.140 in the third wave (all correlations statistically significant, $p < 0.001$). Pair-wise comparisons between respondents with different economic expectations reveal statistically significant differences in their willingness to take risks. As presented in Table 4.2, Mann-Whitney tests indicate that the respondents with positive economic expectations are more willing to take risks than the respondents who have neutral or negative economic expectations. Interestingly, the tests also point to a statistically significant difference between those who expect the economic environment to improve a lot and those who expect it to improve a little.

TABLE 4.2: MEAN WILLINGNESS TO TAKE RISKS, BY ECONOMIC EXPECTATIONS OF THE RESPONDENTS

		The overall economic environment in my community will...				
		(a) Decline a lot	(b) Decline a little	(c) Remain the same	(d) Improve a little	(e) Improve a lot
Willingness to take risks	Wave 1	2.79 [2.33; 3.26]	2.95 [2.66; 3.25]	2.84 ^e [2.72; 2.96]	2.94 ^e [2.84; 3.03]	3.21 ^{c,d} [3.09; 3.34]
	Wave 2	2.78 ^{d,e} [2.47; 3.08]	3.02 ^{d,e} [2.84; 3.21]	3.06 ^{d,e} [2.94; 3.17]	3.35 ^{a,b,c,e} [3.25; 3.45]	3.75 ^{a,b,c,d} [3.60; 3.91]
	Wave 3	3.15 ^{d,e} [2.90; 3.4]	3.37 ^e [3.17; 3.58]	3.37 ^e [3.24; 3.50]	3.59 ^{a,e} [3.49; 3.69]	3.95 ^{a,b,c,d} [3.80; 4.09]

Notes: The table reports means and 95% confidence intervals (in brackets) for the willingness to take risks, conditional on the economic expectations of the respondents. The willingness to take risks is measured on a 5-point scale, with 1 indicating the lowest willingness to take risks, and 5 indicating the highest willingness to take risks. Within each wave, superscripts denote a statistically significant difference in a Mann-Whitney test relative to the column indicated by the superscript (Bonferroni corrected $\alpha = 0.005$). The number of observations is 2632 for Wave 1, 2191 for Wave 2, and 2034 for Wave 3.

TABLE 4.3: MEAN WILLINGNESS TO TAKE RISKS, BY HEALTH EXPECTATIONS OF THE RESPONDENTS

		My health next year will be...				
		(a) Much worse than today	(b) Worse than today	(c) Same as today	(d) Better than today	(e) Much better than today
Willingness to take risks	Wave 1	3.35 [2.25; 4.46]	2.49 ^{d,e} [2.22; 2.77]	2.67 ^{d,e} [2.55; 2.78]	3.00 ^{b,c,e} [2.90; 3.10]	3.39 ^{b,c,d} [3.27; 3.52]
	Wave 2	2.12 ^{c,d,e} [1.43; 2.8]	2.47 ^{c,d,e} [2.20; 2.74]	3.25 ^{a,b} [3.13; 3.37]	3.26 ^{a,b,e} [3.16; 3.35]	3.47 ^{a,b,d} [3.34; 3.61]
	Wave 3	2.81 [1.29; 4.34]	2.78 ^{c,d,e} [2.48; 3.07]	3.38 ^{b,e,f} [3.27; 3.49]	3.67 ^{b,c,e} [3.57; 3.78]	3.81 [3.67; 3.95]

Notes: The table reports means and 95% confidence intervals (in brackets) for the willingness to take risks, conditional on the health expectations of the respondents. The willingness to take risks is measured on a 5-point scale, with 1 indicating the lowest willingness to take risks, and 5 indicating the highest willingness to take risks. Within each wave, superscripts denote a statistically significant difference in a Mann-Whitney test relative to the column indicated by the superscript (Bonferroni corrected $\alpha = 0.005$). The number of observations is 2632 for Wave 1, 2191 for Wave 2, and 2034 for Wave 3.

A similar picture emerges from Table 4.3, which presents the mean willingness to take risks conditional on the health expectations of the respondents. Those with better health expectations are on average more willing to take risks, with the Spearman rank correlation between the two variables being 0.169 in the first wave, 0.108 in the second wave, and 0.147 in the third wave (all correlations statistically significant, $p < 0.001$). Again, Mann-Whitney tests show statistically significant differences: (i) between those with positive expectations and those with negative expectations; (ii) among the two groups with positive expectations; and (iii) those who expect their health to remain the same and those who expect their health to deteriorate. This last difference is mostly visible in the data from waves 2 and 3.

4.3.2 Regression analysis

4.3.2.1 The effects of economic and health expectations

The conditional means presented in the previous section suggest that better economic and health expectations are associated with a higher willingness to take risks. We now turn to regression analysis to examine whether this result holds when we control for a set of covariates that may affect the willingness to take risks and also an individual's expectations. In Table 4.4 we present the main regression results from fixed effects estimation of the model described in equation 4.1 (the complete regression results are provided in the Appendix, in Table A.1).³ All the empirical specifications include economic expectations and health expectations as explanatory variables for the willingness to take risks. In column (1) we include as additional covariates a set of dummy variables to indicate the survey wave, which we use to control for potential time-variant effects that might be present for all respondents. In column (2) we expand the baseline specification by also including variables for the respondents' age, education, marital status, physical and mental health, wealth, and life satisfaction.

The results shows that economic and health expectations significantly predict the willingness to take risk, and in both cases better expectations are associated with a higher willingness to take risk. For economic expectations, the estimated coefficient (0.059, column 2) implies that a change in expectations proportional to their average within-respondent standard deviation is associated with an increase in the willingness

³For the sake of completeness, in Appendix Table A.2 we present results from pooled OLS and ordered logit regressions. While these regression setups do not account for time-invariant individual heterogeneity that can potentially be correlated with our explanatory variables, the results are consistent with those obtained in our main analysis.

TABLE 4.4: THE EFFECTS OF ECONOMIC AND HEALTH EXPECTATIONS ON THE WILLINGNESS TO TAKE RISKS

	(1)	(2)	(3)	(4)
Economic expectations	0.062*** (0.023)	0.059** (0.023)	0.059** (0.028)	0.108*** (0.033)
Health expectations	0.070** (0.028)	0.062** (0.028)	0.060* (0.034)	0.043 (0.042)
Business owner			0.088 (0.777)	
Business owner x Economic expectations			-0.002 (0.049)	
Relocated				-2.773 (5.231)
Relocated x Economic expectations				0.032 (0.153)
Relocated x Health expectations				0.113 (0.200)
Wave dummies	Yes	Yes	Yes	Yes
Sociodemographic controls	No	Yes	Yes	Yes
Observations	6857	6857	6857	4225
R^2	0.044	0.051	0.055	0.055
F -statistic	41.22	13.50	7.24	4.55
$P(F\text{-statistic})$	0.000	0.000	0.000	0.000

Notes: The table reports coefficient estimates and clustered standard errors (in parentheses) from fixed effects regressions. The dependent variable is the willingness to take risks measured on a 5-point scale, with 1 indicating the lowest willingness to take risks, and 5 indicating the highest willingness to take risks. Economic and health expectations are measured on 5-point scales, with 1 indicating the most negative expectations, and 5 indicating the most positive expectations (see the text for details). Sociodemographic controls include variables for age, education, marital status, physical and mental health, wealth, and life satisfaction. Asterisks denote statistical significance: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

to take risks of 4.2% of its average within-respondent standard deviation. Going from the 10th percentile to the 90th percentile of economic expectations implies a difference in the willingness to take risks of 0.18 units. This difference corresponds to about 11% of the unconditional standard deviation of the willingness to take risks. The results for health expectations are similar, but in general the magnitude of the effect is smaller. The estimated coefficient (0.062, column 2) implies that a change in health expectations proportional to their average within-respondent standard deviation is associated with an increase in the willingness to take risks of 3.2% of its average within-respondent standard deviation. Going from the 10th percentile to the 90th percentile of health expectations implies a difference in the willingness to take risks of 0.12 units on the 5-point scale, which corresponds to about 7% of the unconditional standard deviation of the willingness to take risks.

4.3.2.2 Other determinants of risk attitudes

As documented in Appendix Table A.1, we find evidence of a relationship between age and the willingness to take risks, with both the linear and the quadratic terms being statistically significant. The coefficient estimates ($\hat{\delta}_{age} = 0.117$; $\hat{\delta}_{age^2} = -0.0091$) imply that the willingness to take risks increases with age for those younger than 64, and decreases with age for those older than 64. The literature usually documents a negative relationship between age and the willingness to take risks (see, e.g., Pålsson, 1996; Halek and Eisenhauer, 2001; Dohmen et al., 2011), but in many cases the estimated specifications do not include a quadratic term on age. We also find that both marital status and life satisfaction significantly predict the willingness to take risks. Those who are married or living together with their spouse are more willing to take risks, and so are those who are more satisfied with their lives. Similar findings regarding marital status and life satisfaction have also been documented by, e.g., Dohmen et al. (2011). We find no evidence of statistically significant effects related to the education or wealth of the respondents.

4.3.2.3 The effects of business ownership and relocation

Because a substantial proportion of our respondents reports owning a business, we also examine whether business owners are different from non-owners in the way their willingness to take risks responds to changes in expectations. Column (3) of Table 4.4 presents estimation results for a specification similar to that of column (2), but in

which all explanatory variables are interacted with a dummy variable that indicates business ownership. The results suggest that business owners are not different from non-owners: the coefficients on the interaction terms that relate to economic and health expectations are negative but very small (-0.002 and -0.009, respectively), and they are not statistically significant at the 5% level. The main effects retain the original magnitude, with the coefficient on economic expectations being statistically significant with $p < 0.05$, but the coefficient on health expectations being statistically significant only with $p < 0.1$.⁴

We then examine whether the effects of economic and health expectations are different for people who relocate in the periods of time between any two of our interviews. On one hand, those who decide to move may be intrinsically different in their willingness to take risks. On the other hand, those who move may end up in areas that are substantially different from their original area in terms of living conditions or economic opportunities, and this may influence their economic and health expectations. Column (4) of Table 4.4 presents estimation results for a specification similar to that of column (2), but in which all explanatory variables are interacted with a dummy variable that indicates that the respondent has relocated. Because we are only able to detect relocations in the second and third waves of our survey our estimation does not include data from wave 1, hence the smaller number of observations in the panel used for the regression of column 4. The results show no evidence of a difference between those who relocate and those who do not, as the coefficients on the interaction terms that relate to economic and health expectations are not statistically significant.⁵

The estimates for the main effects, however, are considerably different from the ones obtained the other regressions. The coefficient on the economic expectations is almost twice as large as before and statistically significant, and the coefficient on health expectations becomes somewhat smaller and is no longer statistically significant at the 5% level. The differences are not due to estimating this particular specification, but instead result from the fact that we run the estimation on data from the second and third waves. In fact, re-estimating the model of column (2) with that same data yields coefficients for the economic and health expectations that are very close to the ones reported in column (4) for the main effects: 0.110 for the economic expectations ($p = 0.001$), and 0.052 for the health expectations ($p = 0.213$). This suggests that

⁴We obtain similar results with a specification in which the dummy variable that indicates business ownership is interacted only with the expectations variables.

⁵Again, the results hold with a specification in which the dummy variable that indicates relocation is interacted only with the expectations variables.

in the second and third waves of our study the effects of economic expectations are more pronounced, and the effects of health expectations less pronounced.

4.4 Robustness

4.4.1 Measurement of risk attitudes

The results presented in Table 4.4 are from regressions in which the dependent variable is a 5-point measure of the willingness to take risks. In the literature other scales are sometimes used to measure risk attitudes. Some examples are the 11-point scale used by Dohmen et al. (2010) and Dohmen et al. (2011), or the 4-point scale used by Malmendier and Nagel (2011). Scales with a large number of points allow for a more precise characterization of individual risk attitudes and create room for a better measurement of the true variance of risk attitudes that exists in a sample or population. Scales with a smaller number of points aggregate individuals who would rank differently in a scale with a larger number of points, and this may either exaggerate or attenuate differences that exist between any two individuals. For this reason it is important to ask whether the results we have presented so far hold when we use a different scale to measure the willingness to take risks.

In the second and third waves we measured the risk attitudes of our respondents twice, once using a 5-point scale and once using an 11-point scale. The two questions were administered separately at different points of the interview, and the ordering of the questions was randomized for each respondent. In the first column of Table 4.5, we present results from fixed effects estimation of equation 4.1 using the 11-point measure of the willingness to take risks as the dependent variable. The data for the regressions excludes the first wave of the survey because the 11-point measure is not available for that wave. For comparison purposes, we then use the same sub-sample to estimate a regression in which the dependent variable is our original 5-point measure. We present those results in the second column of Table 4.5.

The conclusions are essentially the same for the two measures of the willingness to take risks. We find that economic expectations significantly predict the willingness to take risks, but health expectations do not. For economic expectations the effect sizes are equivalent across the two measures of the willingness to take risks. First, the size of the coefficient estimates relative to the size of the scale is similar across

TABLE 4.5: THE EFFECTS OF ECONOMIC AND HEALTH EXPECTATIONS ON THE WILLINGNESS TO TAKE RISKS, MEASURED ON DIFFERENT SCALES

	DV: Willingness to take risks	
	11-point scale	5-point scale
Economic expectations	0.225*** (0.079)	0.110*** (0.033)
Health expectations	0.013 (0.101)	0.052 (0.042)
Wave dummies	Yes	Yes
Sociodemographic controls	Yes	Yes
Observations	4225	4225
R^2	0.042	0.044
F -statistic	5.28	5.56
$P(F\text{-statistic})$	0.000	0.000

Notes: The table reports coefficient estimates and clustered standard errors (in parentheses) from fixed effects regressions. The dependent variables is the willingness to take risks, measured on an 11-point scale in the first column, and measured on a 5-point scale in the second column. In both cases 1 indicates the lowest willingness to take risks, and the highest number on the scale indicates the highest willingness to take risks. Economic and health expectations are measured on 5-point scales, with 1 indicating the most negative expectations, and 5 indicating the most positive expectations (see the text for details). Sociodemographic controls include variables for age, education, marital status, physical and mental health, wealth, and life satisfaction. Asterisks denote statistical significance: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

our two measures of risk attitudes. In the first column Table 4.5 the estimated coefficient ($\hat{\beta}_1 = 0.225$, $p < 0.001$) implies that a one-unit increase in the measure of economic expectations is associated with an increase of 0.225 points in the measure of risk attitudes. This corresponds to $0.225/11 = 2.05\%$ of the number of points on the 11-point scale of risk attitudes. In the second column the estimated coefficient ($\hat{\beta}_1 = 0.110$, $p < 0.001$) implies that a one-unit increase in the measure of economic expectations is associated with an increase of 0.11 points in the 5-point measure of risk attitudes. This corresponds to $0.110/5 = 2.2\%$ of the number of points on the scale of risk attitudes.

Second, we estimate that an increase in economic expectations by an amount equal to its average within-respondent standard deviation is associated with increases in the willingness to take risks that are similar across the two measurement scales. On the 11-point scale the increase is about 7.3% of the average within-respondent standard deviation observed for that scale. On the 5-point scale the increase is about 8.9% of the average within-respondent standard deviation observed for that scale.

Finally, going from the 10th percentile to the 90th percentile of economic expectations is also associated with increases in the willingness to take risks that are similar across

TABLE 4.6: THE EFFECTS OF ECONOMIC AND HEALTH EXPECTATIONS ON THE WILLINGNESS TO TAKE RISKS, BALANCED PANEL RESULTS

	Balanced sub-panel	Unbalanced panel
Economic expectations	0.062** (0.026)	0.059** (0.023)
Health expectations	0.058* (0.031)	0.062** (0.028)
Observations	4872	6857
R^2	0.057	0.051
F -statistic	11.48	13.50
$P(F\text{-statistic})$	0.000	0.000

Notes: The table reports coefficient estimates and clustered standard errors (in parentheses) from fixed effects regressions. The dependent variables are the willingness to take risks, measured on a 11-point scale (first column) or on a 5-point scale (second column), with 1 indicating the lowest willingness to take risks, and 5 indicating the highest willingness to take risks. Economic and health expectations are measured on 5-point scales, with 1 indicating the most negative expectations, and 5 indicating the most positive expectations (see the text for details). Sociodemographic controls include variables for age, education, marital status, physical and mental health, wealth, and life satisfaction. Asterisks denote statistical significance: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

the two measurement scales. On the 11-point scale the increase corresponds to about 33.7% of the average within-respondent standard deviation observed in our sample. On the 5-point scale the increase corresponds to about 30.7% of the average within-respondent standard deviation observed in our sample.

4.4.2 Survey attrition and non-response

The results we have presented so far are from fixed effects regressions on the unbalanced panel. As we have mentioned in Section 4.3, some of the respondents interviewed in the first wave of the survey were not re-interviewed in subsequent waves, and other respondents did not provide answers to some of the questions asked by our interviewers. In such cases the observations are either missing or have to be excluded from the analysis, leading to a sample selection problem that takes on two forms: (i) attrition, when the respondent completely drops out of the panel; and (ii) a form of incidental truncation, when certain variables are not observed in some periods. Both issues can be safely ignored if they are entirely random, as fixed effects estimation on the unbalanced panel is robust to random sample selection (Wooldridge, 2002, p. 579). But if the sample selection is related to the dependent variable (i.e., correlated with the errors $\varepsilon_{i,t}$ in equation 4.1) we may face a problem of biased coefficient estimates (Hausman and Wise, 1979).

While we should be concerned that sample selection issues might affect our estimates,

there are reasons to believe that the potential bias is likely to be small. Alderman et al. (2001), for example, find that coefficient estimates are not significantly affected by attrition in three longitudinal studies from developing countries, even with attrition rates in excess of 30% between survey waves.⁶ The incidence of attrition in our study is substantially smaller. From the respondents interviewed in the first wave, less than 5% are completely absent from the second and third waves, and about 20% are present in the second wave but absent in the third wave.

We perform a series of statistical tests to check if sample selection is indeed a problem in our data. We first test for the effects of attrition using the method proposed by Beckett et al. (1988). We regress the value of our dependent variable in the first wave, $WTR_{i,1}$, on: (i) the explanatory variables in the first wave; (ii) a dummy variable z_i that takes the value 1 if the respondent subsequently leaves the sample and the value 0 otherwise; and (iii) the interactions between z_i and the other covariates. An F -test for the null that the coefficients of z_i and its interactions with the other covariates are jointly zero provides indication of whether attrition is likely to be a problem. We perform the test and we conclude that we cannot reject the null that all the relevant coefficients are jointly zero ($F = 0.816$, $p = 0.63$), suggesting that the original estimates are unlikely to be biased by the attrition in our panel. Because the third wave of the survey reached out to all the respondents from the first wave, some individuals that were missing in wave 2 re-enter the sample in wave 3 of our study. Even if we remove their observations from the third wave of the unbalanced panel – effectively treating such respondents as having left the study after the first wave – we still find that attrition is unlikely to have any influence on our results. After performing the same F -test as before we find that we still cannot reject the null that all the relevant coefficients are jointly zero ($F = 1.086$, $p = 0.37$).

An alternative way of testing for the effects of sample selection is to use the procedure proposed by Nijman and Verbeek (1992). The procedure consists of using a Hausman test to compare the coefficient estimates from the regression on the unbalanced panel with the coefficient estimates from the regression on the balanced sub-panel. Rejection of the null hypothesis, indicating the presence of significant differences in the coefficients, indicates that the effects of sample selection cannot be dismissed. In the first column of Table 4.6 we present the fixed effects estimates from the sample of respondents who were interviewed in all three waves (i.e., the balanced sub-panel). In the second column of the table we present the estimates obtained with the unbalanced

⁶Alderman et al. (2001) also refer that similar conclusions exist for longitudinal surveys from developed countries, pointing the reader to the results of the studies published in a special issue of the *Journal of Human Resources* titled “Attrition in Longitudinal Surveys” (Spring issue, 1998).

panel.⁷ We can see that for the main variables of interest the coefficient estimates are similar, although the effect of health expectations is not statistically significant at the 5% level on the balanced sub-panel estimation. There are no meaningful differences in the size of the coefficients on other variables (not presented on the table), but: (i) the age variables are no longer statistically significant at the 5% level on the balanced sub-panel ($p_{age} = 0.135$; $p_{agesq} = 0.053$); and (ii) the physical health score becomes statistically significant ($p < 0.05$). Based on the computed Hausman test statistic ($\chi^2(15) = 20.47$, $p = 0.155$) we do not reject the null hypothesis, suggesting that bias from sample selection is unlikely to be a substantial problem in our data.

4.4.3 Autocorrelation

We might be concerned that the disturbances in equation 4.1 are serially correlated across periods. If this is the case, the efficiency of our fixed effects estimates is negatively affected and the inference based on those estimates is invalid. As pointed out by Greene (2012, p. 903), serial correlation in the disturbances can arise when we omit from our model relevant variables that are correlated across time. Serially correlated disturbances might also arise if the dependent variable exhibits some sort of inertia. This is particularly relevant in the context of our study because it is conceivable that risk attitudes might have a fixed component around which they fluctuate slowly over time. To test for serial correlation in the disturbances we use the modified Durbin-Watson statistic proposed by Bhargava et al. (1982), and obtain the value $d_p = 1.76$. While the tables with 5% significance points presented by Bhargava et al. (1982) do not cover the conditions of our particular case, the authors remark (p. 536) that for samples with a large number of individuals researchers can follow a simple rule: check if d_p is less than two when testing for positive serial correlation, or if $4 - d_p$ is less than two when testing for negative serial correlation.⁸

In Table 4.7 we present results from fixed effects regression where the disturbances in equation 4.1 are serially correlated, $\varepsilon_{i,t} = \rho\varepsilon_{i,t-1} + u_{i,t}$, where $u_{i,t}$ is an i.i.d. random variable, $u_{i,t} \sim N(0, \sigma_u^2)$. The number of observations is smaller than in

⁷Because the Hausman test would not be valid with clustered standard errors, the results we present in Table 4.6 do not account for such clustering. A comparison of the results for the unbalanced panel with the equivalent results on Table 4.6 (column 2) shows that the accounting for clustering results in very small changes on the standard errors, with clustered standard errors being larger. However, our conclusions would hold even if the standard errors on Table 4.6 were as large as the clustered standard errors.

⁸In fact, for sample sizes of $n = 1000$ the tables presented by Bhargava et al. (1982) (covering $T = 6$ and $T = 10$) already indicate 5% significance points in excess of 1.95.

TABLE 4.7: THE EFFECTS OF ECONOMIC AND HEALTH EXPECTATIONS ON THE WILLINGNESS TO TAKE RISKS, FIXED EFFECTS ESTIMATES WITH SERIALLY CORRELATED DISTURBANCES

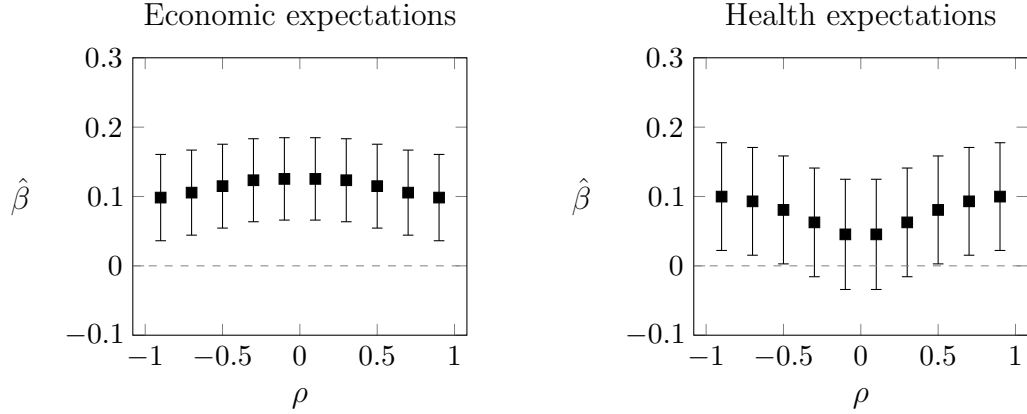
Economic expectations	0.125*** (0.030)
Health expectations	0.049 (0.040)
Observations	4177
R^2	0.032
F -statistic	3.86
$P(F\text{-statistic})$	0.000

Notes: The table reports coefficient estimates and standard errors (in parentheses) from fixed effects regression with AR(1) disturbances. The dependent variable is the willingness to take risks measured on a 5-point scale, with 1 indicating the lowest willingness to take risks, and 5 indicating the highest willingness to take risks. Economic and health expectations are measured on 5-point scales, with 1 indicating the most negative expectations, and 5 indicating the most positive expectations (see the text for details). Sociodemographic controls include variables for age, education, marital status, physical and mental health, wealth, and life satisfaction. Asterisks denote statistical significance: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

the case of no serial correlation (see Table 4.4) because the data is transformed to deal with the autoregressive component of the residuals. We find a statistically significant relationship between economic expectations and the willingness to take risks ($\hat{\beta}_1 = 0.125$, $p < 0.01$), with the estimate for the coefficient on economic expectations being substantially larger than the one we obtain when we ignore the issue of serial correlation ($\hat{\beta}_1 = 0.059$, in column 2 of Table 4.4). As for the coefficient on health expectations, we find that the new estimate ($\hat{\beta}_2 = 0.049$) is smaller than our original estimate ($\hat{\beta}_2 = 0.062$, in column 2 of Table 4.4) and no longer statistically significant at the 5% level. The results suggest that if the disturbances are indeed serially correlated, then our original findings may constitute a conservative estimate of the importance of economic expectations, but may overestimate the importance (and the statistical significance) of the effects of health expectations.

Because our dataset contains a small number of time periods ($T = 3$), we have to consider the possibility that the results of Table 4.7 build on a biased estimate of the autoregressive coefficient ρ . While our estimates indicate that $\hat{\rho} = 0.143$, it is useful to investigate how the results would look like if ρ was to take on other values. This provides a reasonable picture of how robust the results of Table 4.7 are to the structure of the serial correlation. To this end we estimate our model for different values on ρ , and then compare the estimates obtained for the coefficients associated with the expectations variables. In Figure 4.1 we present the coefficient estimates and the corresponding 95% confidence intervals. For economic expectations the estimated

FIGURE 4.1: COEFFICIENT ESTIMATES AND 95% CONFIDENCE INTERVALS FOR THE ECONOMIC AND HEALTH EXPECTATION VARIABLES, UNDER DIFFERENT VALUES OF ρ .



coefficient is always statistically significant at the 5% level, and the magnitude of the coefficient varies little with ρ . For health expectations we find considerably more variation in the coefficient size as ρ varies, and that its statistical significance also changes with ρ . However, the coefficient would only be statistically significant at the 5% level for large absolute values of ρ , $0.5 < |\rho| < 1$, which are far from our baseline estimate, $\hat{\rho} = 0.143$.

4.5 Discussion

4.5.1 Limitations

One potential limitation of our study is that we use survey-based measures of the willingness to take risks, rather than incentive-compatible measures. We may question whether such measures are a good tool to elicit risk attitudes, as they may be too noisy even when respondents provide truthful answers. With respect to this, some studies have successfully used survey-based measures to predict actual risky health behavior (see, e.g., Szrek et al., 2012) and risk-taking behavior in contexts with monetary consequences (see, e.g., Dohmen et al., 2011), thereby providing some validity for their use. A related question is whether respondents provided truthful answers when asked about their willingness to take risks. The data we use in this study does not allow us to answer this question. The most we can learn from the data is that respondents are consistent when they state their willingness to take

risks: the Spearman rank correlation between the 5-point and 11-point measures of risk attitudes is very high and statistically significant ($r_s = 0.932$, $p < 0.001$).

Another limitation relates to how respondents may have interpreted our expectations questions. When asked about their expectations for the economic environment in their communities, some respondents may have interpreted “*economic environment*” as referring to the number of businesses, others may have interpreted it as referring to the income of the households, and yet others may have thought about unemployment or a combination of these (or other) factors. While business activity, household income, unemployment, and other economic indicators are usually correlated and linked to the state of the economy, the different interpretations for “*economic environment*” may potentially add noise to our measure of economic expectations. This is also a concern for the health expectations question. When asked about their expectations for their own health, some respondents may have interpreted it as referring to their physical health, their mental health, or a combination of both. The data, however, shows a statistically significant Spearman rank correlation between health expectations in wave t and the PCS12 scores in wave $t + 1$ ($r_s = 0.098$, $p < 0.001$), but no evidence of a statistically significant Spearman rank correlation between health expectations in wave t and the MCS12 scores in wave $t + 1$ ($r_s = -0.0004$, $p = 0.982$). This suggests respondents may have mostly interpreted the question in terms of their own physical health.

The small number of periods in our dataset limits our ability to properly investigate the issue of serially correlated disturbances. We may detect (and wrongly correct for) serial correlation where there is none, or if serial correlation is indeed present we may obtain poor estimates for the process governing it, and fail to properly correct its effects. Our conclusions about the role of economic expectations are not affected by this issue, as we always find a statistically significant effect regardless of whether serial correlation is indeed present, and regardless of what it might be like. For health expectations, however, this is not the case. Our results suggest the presence (and nature) of serially correlated disturbances may substantially change our conclusions, and as such the limitations of our data become important.

One final limitation of our study relates to the issue of causality. Because we do not have clearly identified exogenous variations in the expectations variables, we cannot rule out that it is the variation in the willingness to take risks that drives the variation in the economic and health expectations. This is particularly relevant for the health expectations, because those who rate themselves as being more willing to take risks may indeed engage in unhealthy risky behavior more frequently, and they

may understand that such behavior is likely to be detrimental to their future health. The direction of causality is perhaps less controversial with respect to economic expectations. The economic environment of the communities where we conducted our interviews is influenced by factors that are, to a large extent, exogenous from the perspective of our respondents. Factors such as political and economic conditions at the national level, and price developments in international markets are likely to directly affect the economic conditions of the communities where the respondents live. To the extent that our respondents understand such relationships, some of the variation observed in economic expectations is probably exogenous. Furthermore, it is unlikely that the individual actions and choices of our respondents have an appreciable effect in the economic environment of their communities. Respondents may therefore think that their willingness to take risks does not affect the economic outlook for their communities.

4.5.2 Policy implications

Attitudes towards risk play a key role in many choices that individuals make, such as when deciding whether or not to pursue a risky recreational activity, whether or not to open a business, or whether or not to invest in a risky asset. While expectations may influence such decisions directly, our results suggest that expectations may also influence such decisions by shaping attitudes towards risk. The presence of such mechanism has important policy implications.

Our results suggest that when people anticipate good economic conditions they become more willing to take risks. During an expansion, economic risk taking then increases in response to better expected returns but also in response to the shift in expectations. For individuals like those in our sample, who face a paucity of jobs and who often turn to small entrepreneurial ventures to make a living, this might result in excess entry and, subsequently, in higher rates of business failure. During a contraction, economic risk taking then decreases in response to worse expected returns but also in response to the shift in expectations. For individuals like those in our sample, this might stifle their entrepreneurial activity more than if risk attitudes had remained unchanged, compounding on the negative effects of job destruction that take place in a downturn.

Conditional on the external validity of our study, the results related to economic expectations may also provide a new perspective of investor behavior and contribute

to improve our understanding of asset bubbles. Our study suggests that positive information about the economy may feed into investor behavior not only by raising expected returns, but also by increasing the willingness to take risks. This points to the possibility that asset prices are partially driven by a self-reinforcing mechanism. During an economic expansion investors bid up asset prices because of better expected returns, but do it to a greater extent than if risks attitudes had remained unchanged. Asset prices increases may themselves be perceived as additional positive information about the economy, further contributing to increase the investors' willingness to take risks, and consequently they exert additional upwards pressure on asset prices. During an economic contraction the mechanism works in the opposite direction, and acts to exert an additional downwards pressure on asset prices that would not exist had risk attitudes remained unchanged. Asset boom and bust cycles may thus be partly driven by a *rational* response of investors to shifts in risk attitudes caused by good or bad economic news. This question is relevant because large swings in asset prices are often an important source of macroeconomic fluctuations, and there is considerable debate about whether monetary policy should respond to such movements in asset prices (see, e.g., Bernanke and Gertler, 2001; Leduc and Natal, 2016; Mishkin, 2017). The presence of a mechanism such as the one suggested by our results would provide a rationale for policy interventions aimed at shaping investors' expectations.

To a lesser extent, our results suggest that improving the health expectations of individuals may also increase their willingness to take risks. This finding is relevant for the discussion of policy interventions in many Sub-Saharan African countries, as they sometimes face public health challenges and economic challenges simultaneously. Public health interventions which improve health conditions and health expectations may also contribute to increase the willingness to take risks in the population, and contribute to encourage entrepreneurial risk taking. Because individuals in those countries often face a paucity of jobs and turn to small business ownership to make a living, the increase in entrepreneurial activity potentially spurred by the improvement in health expectations is something that should not be overlooked by policymakers when deciding about public health interventions.

4.6 Conclusion

In this paper, we used data from a longitudinal survey conducted in the Tshwane Municipality, South Africa, to study how economic and health expectations relate to

a measure of willingness to take risks. We found economic expectations significantly predict the willingness to take risks: individuals who have better expectations for the economic environment of their community report a higher willingness to take risks. The evidence regarding the relationship between health expectations and the willingness to take risks is less conclusive. In our main regressions, we found that better health expectations significantly predict our 5-point measure of risk attitudes: individuals with better expectations for their own health status report a higher willingness to take risks. However, we found that the result does not hold in a regression that uses a 10-point measure of risk attitudes as dependent variable (available for a sub-sample of observations), nor in a series of robustness checks.

The results highlight an indirect channel through which economic expectations may influence decision making under risk, as risk attitudes have been shown to predict risk taking behavior in many contexts (see, e.g., Hanoch et al., 2006; Szrek et al., 2012). However, in our study we do not directly examine whether expectations significantly predict decision making under risk, and a potential next step is to examine this issue using either data from people’s decisions in everyday life contexts where risk plays a role, or data from incentive-compatible measures of risk attitudes.

As highlighted in Section 4.2, our study compares a measure of risk attitudes in general with measures of expectations in two specific domains, and in some circumstances this may limit our ability to detect a relationship between expectations and risk attitudes. Thus, future research may also re-examine the issues addressed in our study using domain-specific measures of expectations and domain-specific measures of the willingness to take risks. Furthermore, a study with domain-specific measures could also allow us to understand whether our results reflect a relationship between expectations and risk attitudes that, although detectable with a measure of risk attitudes in general, is domain specific, or whether the expectations exhibit a relationship with risk attitudes in general.

Appendix

TABLE A.1: THE EFFECTS OF ECONOMIC AND HEALTH EXPECTATIONS ON THE WILLINGNESS TO TAKE RISKS (FULL REGRESSIONS)

	(1)	(2)	(3)	(4)
Economic expectations	0.062*** (0.023)	0.059** (0.023)	0.059** (0.028)	0.108*** (0.033)
Health expectations	0.070** (0.028)	0.062** (0.028)	0.060* (0.034)	0.043 (0.042)
Age		0.117** (0.059)	0.120** (0.059)	0.116 (0.139)
Age squared		-0.001** (0.000)	-0.001** (0.000)	-0.001 (0.001)
PCS12 score		0.005 (0.003)	0.001 (0.004)	0.006 (0.006)
MCS12 score		-0.001 (0.003)	0.000 (0.003)	-0.002 (0.004)
Life satisfaction		0.003*** (0.001)	0.003*** (0.001)	0.003 (0.002)
Marital status		0.217*** (0.079)	0.256*** (0.092)	0.313** (0.135)
Primary schooling completed		0.137 (0.273)	0.165 (0.339)	0.072 (0.379)
Some secondary schooling		-0.049 (0.379)	-0.026 (0.404)	0.545 (0.605)
Secondary schooling completed		0.005 (0.414)	0.006 (0.440)	0.941 (0.660)
Above secondary schooling		0.231 (0.446)	0.225 (0.472)	1.577** (0.758)
Wealth index		0.005 (0.023)	0.010 (0.028)	0.048 (0.044)
Wave 2 dummy	0.281*** (0.042)	0.190 (0.128)	0.132 (0.131)	
Wave 3 dummy	0.582*** (0.046)	0.415** (0.186)	0.382** (0.188)	0.234** (0.119)

(continues)

TABLE A.1: THE EFFECTS OF ECONOMIC AND HEALTH EXPECTATIONS ON THE WILLINGNESS TO TAKE RISKS (FULL REGRESSIONS, CONTINUED)

	(1)	(2)	(3)	(4)
Business owner			0.088 (0.777)	
Business owner x Economic expectations			-0.002 (0.049)	
Business owner x Health expectations			-0.009 (0.057)	
Business owner x Age			-0.012 (0.025)	
Business owner x Age squared			0.000 (0.000)	
Business owner x PCS12 score			0.012* (0.006)	
Business owner x MCS12 score			-0.005 (0.005)	
Business owner x Life satisfaction			-0.002 (0.002)	
Business owner x Marital status			-0.106 (0.124)	
Business owner x Primary schooling completed			-0.096 (0.318)	
Business owner x Some secondary schooling			-0.015 (0.254)	
Business owner x Secondary schooling completed			0.062 (0.281)	
Business owner x Above secondary schooling			0.097 (0.314)	
Business owner x Wealth index			-0.018 (0.041)	
Business owner x Wave 2 dummy			0.151 (0.098)	
Business owner x Wave 3 dummy			0.101 (0.113)	
<i>(continues)</i>				

TABLE A.1: THE EFFECTS OF ECONOMIC AND HEALTH EXPECTATIONS ON THE WILLINGNESS TO TAKE RISKS (FULL REGRESSIONS, CONTINUED)

	(1)	(2)	(3)	(4)
Relocated				-2.773 (5.231)
Relocated x Economic expect.				0.032 (0.153)
Relocated x Health expect.				0.113 (0.200)
Relocated x Age				0.328* (0.192)
Relocated x Age squared				-0.004 (0.002)
Relocated x PCS12 score				-0.016 (0.032)
Relocated x MCS12 score				-0.017 (0.020)
Relocated x Life satisfaction				0.002 (0.007)
Relocated x Marital status				-0.302 (0.425)
Relocated x Primary schooling completed				—
Relocated x Some secondary schooling				-1.984*** (0.676)
Relocated x Secondary schooling completed				-2.454*** (0.701)
Relocated x Above secondary schooling				-1.498* (0.774)
Relocated x Wealth index				0.075 (0.102)
Relocated x Wave 3 dummy				-0.599** (0.280)
Constant	2.479*** (0.134)	-1.031 (2.122)	-1.005 (2.130)	-0.947 (4.348)
Observations	6857	6857	6857	4225
R^2	0.044	0.051	0.055	0.055
F -statistic	41.22	13.50	7.24	4.55
$P(F$ -statistic)	0.000	0.000	0.000	0.000

Notes: The table reports coefficient estimates and clustered standard errors (in parentheses) from fixed effects regressions. The dependent variable is the willingness to take risks measured on a 5-point scale, with 1 indicating the lowest willingness to take risks, and 5 indicating the highest willingness to take risks. Economic and health expectations are measured on 5-point scales, with 1 indicating the most negative expectations, and 5 indicating the most positive expectations (see the text for details). In regression (4) the coefficient on the interaction between the relocation dummy and the dummy that indicates completion of primary schooling cannot be estimated because the number of observations is insufficient. Asterisks denote statistical significance: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

TABLE A.2: THE EFFECTS OF ECONOMIC AND HEALTH EXPECTATIONS ON THE WILLINGNESS TO TAKE RISKS, POOLED OLS AND ORDERED LOGIT ESTIMATES

	Pooled OLS		Pooled ordinal logit	
	(1)	(2)	(3)	(4)
Economic expectations	0.148*** (0.020)	0.116*** (0.019)	1.195*** (0.028)	1.156*** (0.028)
Health expectations	0.237*** (0.023)	0.122*** (0.023)	1.314*** (0.037)	1.159*** (0.033)
Age		0.025*** (0.007)		1.036*** (0.010)
Age squared		-0.000*** (0.000)		0.999*** (0.000)
PCS12 score		0.017*** (0.003)		1.022*** (0.003)
MCS12 score		0.004** (0.002)		1.005** (0.002)
Life satisfaction		0 (0.001)		1.000 (0.001)
Marital status		0.098** (0.043)		1.117** (0.059)
Primary education completed		-0.006 (0.107)		0.991 (0.136)
Some secondary education		0.103 (0.067)		1.117 (0.093)
Secondary education completed		0.205** (0.079)		1.282** (0.127)
Above secondary education		0.401*** (0.085)		1.509*** (0.158)
Wealth index		0.024* (0.014)		1.026 (0.018)
Wave 2 dummy	0.336*** (0.041)	0.287*** (0.042)	1.445*** (0.070)	1.366*** (0.070)
Wave 3 dummy	0.647*** (0.044)	0.577*** (0.046)	2.105*** (0.113)	1.978*** (0.113)
Constant	1.504*** (0.113)	0.627** (0.264)	2.327*** (0.320)	8.091*** (2.722)
Observations	6857	6857	6857	6857
R^2	0.052	0.122		
F -statistic	91.96	69.40		
$P(F\text{-statistic})$	0.000	0.000	0.000	0.000
Wald χ^2	—	—	320.02	710.23
$P(\text{Wald } \chi^2)$	—	—	0.000	0.000

Notes: The table reports coefficient estimates and clustered standard errors (in parentheses) from pooled OLS (columns 1 and 2) and pooled ordered logit (columns 3 and 4) regressions. The dependent variable is the willingness to take risks measured on a 5-point scale, with 1 indicating the lowest willingness to take risks, and 5 indicating the highest willingness to take risks. Economic and health expectations are measured on 5-point scales, with 1 indicating the most negative expectations, and 5 indicating the most positive expectations (see the text for details). Sociodemographic controls include variables for age, education, marital status, physical and mental health, wealth, and life satisfaction. Asterisks denote statistical significance: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Bibliography

- Abel, A. B. (1990). Asset prices under habit formation and catching up with the Joneses. *American Economic Review*, 80(2):38–42.
- Acemoglu, D. (2003). Cross-country inequality trends. *Economic Journal*, 113(485):F121–F149.
- Alderman, H., Behrman, J. R., Kohler, H.-P., Maluccio, J. A., and Watkins, S. C. (2001). Attrition in longitudinal household survey data. *Demographic Research*, 5(4):79–124.
- Ambler, S., Cardia, E., and Zimmermann, C. (2004). International business cycles: What are the facts? *Journal of Monetary Economics*, 51(2):257–276.
- Armington, P. S. (1969). A theory of demand for products distinguished by place of production. *International Monetary Fund Staff Papers*, 16(1):159–78.
- Attanasio, P. O. and Weber, G. (1989). Intertemporal substitution, risk aversion and the euler equation for consumption. *Economic Journal*, 99:59–73.
- Autor, D. H., Katz, L. F., and Kearney, M. S. (2008). Trends in U.S. wage inequality: Revising the revisionists. *Review of Economics and Statistics*, 90(2):300–323.
- Backus, D. K., Kehoe, P. J., and Kydland, F. E. (1994). Dynamics of the trade balance and the terms of trade: The J-curve? *American Economic Review*, 84(1):84–103.
- Backus, D. K., Kehoe, P. J., and Kydland, F. E. (1995). International business cycles: theory and evidence. In Cooley, T. F., editor, *Frontiers of Business Cycle Research*, pages 331–356. Princeton University Press.
- Backus, D. K. and Smith, G. W. (1993). Consumption and real exchange rates in dynamic economies with non-traded goods. *Journal of International Economics*, 35:297–316.

- Bansal, R. and Yaron, A. (2004). Risks for the long run: A potential resolution of asset pricing puzzles. *Journal of Finance*, 59(4):1481–1509.
- Barseghyan, L., Prince, J., and Teitelbaum, J. C. (2011). Are risk preferences stable across contexts? Evidence from insurance data. *American Economic Review*, 101(2):591–631.
- Beber, A. and Brandt, M. W. (2006). The effect of macroeconomic news on beliefs and preferences: Evidence from the options market. *Journal of Monetary Economics*, 53(8):1997–2039.
- Beckett, S., Gould, W., Lillard, L., and Welch, F. (1988). The Panel Study of Income Dynamics after fourteen years: An evaluation. *Journal of Labor Economics*, 6(4):472–492.
- Benigno, G., Benigno, P., and Nisticò, S. (2011). Risk, monetary policy and the exchange rate. In *NBER Macroeconomics Annual*, volume 26, pages 247–309. National Bureau of Economic Research.
- Berman, E., Bound, J., and Machin, S. (1998). Implications of skill-biased technological change: International evidence. *Quarterly Journal of Economics*, 113(4):1245–1279.
- Bernanke, B. S. and Gertler, M. (2001). Should central banks respond to movements in asset prices? *American Economic Review*, 91(2):253–257.
- Bhargava, A., Franzini, L., and Narendranathan, W. (1982). Serial correlation and the fixed effects model. *Review of Economic Studies*, 49(4):533–549.
- Bjork, J. M., Knutson, B., Fong, G. W., Caggiano, D. M., Bennett, S. M., and Homer, D. W. (2004). Incentive-elicited brain activation in adolescents: Similarities and differences from young adults. *Journal of Neuroscience*, 24(8):1793–1802.
- Bollerslev, T., Gibson, M., and Zhou, H. (2011). Dynamic estimation of volatility risk premia and investor risk aversion from option-implied and realized volatilities. *Journal of Econometrics*, 160(1):235–245.
- Byrnes, J. P., Miller, D. C., and Schafer, W. D. (1999). Gender differences in risk taking: A meta-analysis. *Psychological Bulletin*, 125(3):367–383.
- Caldara, D., Fernandez-Villaverde, J., Rubio-Ramírez, J. F., and Yao, W. (2012). Computing DSGE models with recursive preferences and stochastic volatility. *Review of Economic Dynamics*, 15(2):188–206.

- Caliendo, M., Fossen, F. M., and Kritikos, A. S. (2009). Risk attitudes of nascent entrepreneurs – New evidence from an experimentally validated survey. *Small Business Economics*, 32(2):153–167.
- Callen, M., Isaqzadeh, M., Long, J. D., and Sprenger, C. (2014). Violence and risk preference: Experimental evidence from Afghanistan. *American Economic Review*, 104(1):123–148.
- Cameron, L. and Shah, M. (2015). Risk-taking behavior in the wake of natural disasters. *Journal of Human Resources*, 50(2):484–515.
- Campbell, J. Y. and Cochrane, J. (1999). By force of habit: A consumption-based explanation of aggregate stock market behavior. *Journal of Political Economy*, 107(2):205–251.
- Cassar, A., Healy, A., and Von Kessler, C. (2011). Trust, risk, and time preferences after a natural disaster: Experimental evidence from Thailand. *Unpublished manuscript*.
- Castro, R. and Coen-Pirani, D. (2008). Why have skilled hours become so cyclical since the mid-1980s? *International Economic Review*, 49(1):135–185.
- Çenesiz, A. and Guimarães, L. (2017). Investment in skill variety and unemployment volatility. *Unpublished manuscript*.
- Cesarini, D., Dawes, C. T., Johannesson, M., Lichtenstein, P., and Wallace, B. (2009). Genetic variation in preferences for giving and risk taking. *Quarterly Journal of Economics*, 124(2):809–842.
- Champagne, J. and Kurmann, A. (2013). The great increase in relative wage volatility in the United States. *Journal of Monetary Economics*, 60(2):166–183.
- Chao, L.-W., Szrek, H., Peltzer, K., Ramlagan, S., Fleming, P., Leite, R., Magerman, J., Ngwenya, G. B., Pereira, N. S., and Behrman, J. (2012). A comparison of EPI sampling, probability sampling, and compact segment sampling methods for micro and small enterprises. *Journal of Development Economics*, 98(1):94–107.
- Chari, V. V., Kehoe, P. J., and McGrattan, E. R. (2002). Can sticky price models generate volatile and persistent real exchange rates? *Review of Economic Studies*, 69(3):533–563.
- Chassamboulli, A. (2011). Cyclical upgrading of labor and employment differences across skill groups. *B.E. Journal of Macroeconomics*, 11(1):Article 14.

- Chetty, R., Guren, A., Manoli, D., and Weber, A. (2011). Are micro and macro labor supply elasticities consistent? A review of evidence on the intensive and extensive margins. *American Economic Review*, 101(3):471—475.
- Chiappori, P.-A., Iyigun, M., and Weiss, Y. (2009). Investment in schooling and the marriage market. *American Economic Review*, 99(5):1689–1713.
- Chongvilaivan, A., Hur, J., and Riyanto, Y. E. (2009). Outsourcing types, relative wages, and the demand for skilled workers: New evidence from U.S. manufacturing. *Economic Inquiry*, 47(1):18–33.
- Chua, P., Krams, M., Toni, I., Passingham, R., and Dolan, R. (1999). A functional anatomy of anticipatory anxiety. *Neuroimage*, 9(6):563–571.
- Coates, J. M. and Herbert, J. (2008). Endogenous steroids and financial risk taking on a london trading floor. *Proceedings of the National Academy of Sciences*, 105(16):6167–6172.
- Cohn, A., Engelmann, J., Fehr, E., and Maréchal, M. A. (2015). Evidence for countercyclical risk aversion: An experiment with financial professionals. *American Economic Review*, 105(2):860—885.
- Colacito, R. and Croce, M. M. (2011). Risks for the long run and the real exchange rate. *Journal of Political Economy*, 119(1):153–181.
- Colacito, R. and Croce, M. M. (2013). International asset pricing with recursive preferences. *Journal of Finance*, 68(6):2651–2686.
- Corsetti, G., Dedola, L., and Leduc, S. (2008). International risk sharing and the transmission of productivity shocks. *Review of Economic Studies*, 75(2):443–473.
- Cramer, J. S., Hartog, J., Jonker, N., and Van Praag, C. M. (2002). Low risk aversion encourages the choice for entrepreneurship: An empirical test of a truism. *Journal of Economic Behavior & Organization*, 48(1):29–36.
- Croson, R. and Gneezy, U. (2009). Gender differences in preferences. *Journal of Economic Literature*, 47(2):448–474.
- Cutler, D. and Lleras-Muney, A. (2008). *Education and Health: Evaluating Theories and Evidence*. Russell Sage Foundation, New York.
- Dmitriev, A. and Roberts, I. (2012). International business cycles with complete markets. *Journal of Economic Dynamics and Control*, 36(6):862–875.

- Dohmen, T., Falk, A., Huffman, D., and Sunde, U. (2010). Are risk aversion and impatience related to cognitive ability? *American Economic Review*, 100(3):1238–1260.
- Dohmen, T., Falk, A., Huffman, D., Sunde, U., Schupp, J., and Wagner, G. G. (2011). Individual risk attitudes: Measurement, determinants, and behavioral consequences. *Journal of the European Economic Association*, 9(3):522–550.
- Eckel, C. C., El-Gamal, M., and Wilson, R. K. (2009). Risk loving after the storm: A Bayesian-network study of hurricane Katrina evacuees. *Journal of Economic Behavior & Organization*, 69(2):110–124.
- Einav, L., Finkelstein, A., Pascu, I., and Cullen, M. R. (2012). How general are risk preferences? Choices under uncertainty in different domains. *American Economic Review*, 102(6):2606–2638.
- Ekelund, J., Johansson, E., Järvelin, M.-R., and Lichtermann, D. (2005). Self-employment and risk aversion – Evidence from psychological test data. *Labour Economics*, 12(5):649–659.
- Epstein, L. G. and Zin, S. E. (1989). Substitution, risk aversion, and the temporal behavior of consumption and asset returns: A theoretical framework. *Econometrica*, 57(4):937–969.
- Fama, E. (1984). Forward and spot exchange rates. *Journal of Monetary Economics*, 14(3):319–338.
- Gertler, M. and Trigari, A. (2009). Unemployment fluctuations with staggered Nash wage bargaining. *Journal of Political Economy*, 117(1):38–86.
- Goebel, J., Krekel, C., Tiefenbach, T., and Ziebarth, N. R. (2015). How natural disasters can affect environmental concerns, risk aversion, and even politics: Evidence from Fukushima and three European countries. *Journal of Population Economics*, 28(4):1137–1180.
- Gourio, F., Siemer, M., and Verdelhan, A. (2013). International risk cycles. *Journal of International Economics*, 89(2):471–484.
- Greenberg, A. E. (2013). When imagining future wealth influences risky decision making. *Judgment and Decision Making*, 8(3):268–277.
- Greene, W. H. (2012). *Econometric Analysis*. Prentice Hall, 7th edition.

- Greenwood, J., Hercowitz, Z., and Huffman, G. W. (1988). Investment, capacity utilization, and the real business cycle. *American Economic Review*, 78(3):402–417.
- Guiso, L. and Paiella, M. (2008). Risk aversion, wealth, and background risk. *Journal of the European Economic Association*, 6(6):1109–1150.
- Guiso, L., Sapienza, P., and Zingales, L. (2013). Time-varying risk aversion. Technical Report 19284, National Bureau of Economic Research.
- Guvenen, F. (2006). Reconciling conflicting evidence on the elasticity of intertemporal substitution: A macroeconomic perspective. *Journal of Monetary Economics*, 53(7):1451–1472.
- Guvenen, F. (2009). A parsimonious macroeconomic model for asset pricing. *Econometrica*, 77(6):1711–1750.
- Hagedorn, M. and Manovskii, I. (2008). The cyclical behavior of equilibrium unemployment and vacancies revisited. *American Economic Review*, 98(4):1692–1706.
- Hagedorn, M., Manovskii, I., and Stetsenko, S. (2016). Taxation and unemployment in models with heterogeneous workers. *Review of Economic Dynamics*, 19:161–189.
- Halek, M. and Eisenhauer, J. G. (2001). Demography of risk aversion. *Journal of Risk and Insurance*, 68(1):1–24.
- Hall, R. E. (1988). Intertemporal substitution in consumption. *Journal of Political Economy*, 96(2):339–357.
- Hall, R. E. and Milgrom, P. R. (2008). The limited influence of unemployment on the wage bargain. *American Economic Review*, 98(4):1653–1674.
- Hanaoka, C., Shigeoka, H., and Watanabe, Y. (2015). Do risk preferences change? Evidence from panel data before and after the Great East Japan Earthquake. Working Paper 21400, National Bureau of Economic Research.
- Hanoch, Y., Johnson, J. G., and Wilke, A. (2006). Domain specificity in experimental measures and participant recruitment. *Psychological Science*, 17(4):300–304.
- Hansen, L. P. and Singleton, K. (1982). Generalized instrumental variables estimation of nonlinear rational expectations models. *Econometrica*, 50:1269–1286.
- Harbaugh, W. T., Krause, K., and Vesterlund, L. (2002). Risk attitudes of children and adults: Choices over small and large probability gains and losses. *Experimental Economics*, 5(1):53–84.

- Hartog, J., Ferrer-i Carbonell, A., and Jonker, N. (2002). Linking measured risk aversion to individual characteristics. *Kyklos*, 55(1):3–26.
- Hausman, J. A. and Wise, D. A. (1979). Attrition bias in experimental and panel data: the Gary income maintenance experiment. *Econometrica*, 47(2):455–473.
- Heathcote, J. and Perri, F. (2002). Financial autarky and international business cycles. *Journal of Monetary Economics*, 49(3):601–627.
- Heathcote, J., Perri, F., and Violante, G. L. (2010). Unequal we stand: An empirical analysis of economic inequality in the United States, 1967–2006. *Review of Economic Dynamics*, 13(1):15–51.
- Hodrick, R. J. and Prescott, E. C. (1997). Postwar u.s. business cycles: An empirical investigation. *Journal of Money, Credit and Banking*, 29(1):1–16.
- Hoffmann, A. O., Post, T., and Pennings, J. M. (2013). Individual investor perceptions and behavior during the financial crisis. *Journal of Banking & Finance*, 37:60–74.
- Hryshko, D., Luengo-Prado, M. J., and Sørensen, B. E. (2011). Childhood determinants of risk aversion: The long shadow of compulsory education. *Quantitative Economics*, 2(1):37–72.
- Judd, K. L. (1996). Approximation, perturbation, and projection methods in economic analysis. In *Handbook of Computational Economics*, volume 1, pages 509–585. Elsevier.
- Judd, K. L. and Guu, S. M. (1992). Perturbation solution methods for economic growth models. In Varian, H., editor, *Economic and Financial Modelling with Mathematica*. Springer-Verlag.
- Judd, K. L. and Guu, S. M. (1997). Asymptotic methods for aggregate growth models. *Journal of Economic Dynamics and Control*, 21:1025–1042.
- Kahneman, D. and Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, 47(2):263–291.
- Kan, K. and Tsai, W.-D. (2006). Entrepreneurship and risk aversion. *Small Business Economics*, 26(5):465–474.
- Kandasamy, N., Hardy, B., Page, L., Schaffner, M., Graggaber, J., Powlson, A. S., Fletcher, P. C., Gurnell, M., and Coates, J. (2014). Cortisol shifts financial risk preferences. *Proceedings of the National Academy of Sciences*, 111(9):3608–3613.

- Katz, L. F. and Murphy, K. M. (1992). Changes in relative wages, 1963-1987: Supply and demand factors. *Quarterly Journal of Economics*, 107(1):35–78.
- Kennan, J. (2010). Private information, wage bargaining and employment fluctuations. *Review of Economic Studies*, 77(2):633–664.
- Kim, C.-J. and Nelson, C. R. (1999). Has the U.S. economy become more stable? A bayesian approach based on markov-switching model of the business cycle. *Review of Economics and Statistics*, 81(4):608–616.
- Kim, K. H. (2014). Counter-cyclical risk aversion. *Journal of Empirical Finance*, 29:384–401.
- Kim, Y.-I. and Lee, J. (2014). The long-run impact of a traumatic experience on risk aversion. *Journal of Economic Behavior & Organization*, 108:174–186.
- Kreps, D. M. and Porteus, E. L. (1978). Temporal resolution of uncertainty and dynamic choice theory. *Econometrica*, 46(1):185–200.
- Krusell, P., Ohanian, L. E., Ríos-Rull, J.-V., and Violante, G. L. (2000). Capital-skill complementarity and inequality: A macroeconomic analysis. *Econometrica*, 68(5):1029–1053.
- Kuhnen, C. M. and Chiao, J. Y. (2009). Genetic determinants of financial risk taking. *PLoS ONE*, 4(2):e4362.
- Kuhnen, C. M. and Knutson, B. (2005). The neural basis of financial risk taking. *Neuron*, 47(5):763–770.
- Kuhnen, C. M. and Knutson, B. (2011). The influence of affect on beliefs, preferences, and financial decisions. *Journal of Financial and Quantitative Analysis*, 46(3):605–626.
- Leduc, S. and Natal, J.-M. (2016). Monetary and macroprudential policies in a leveraged economy. *Economic Journal*, Forthcoming.
- Lewis, S. K. and Oppenheimer, V. K. (2000). Educational assortative mating across marriage markets: Nonhispanic whites in the United States. *Demography*, 37(1):29–40.
- Lindquist, M. J. (2004). Capital-skill complementarity and inequality over the business cycle. *Review of Economic Dynamics*, 7(3):519–540.

- Machin, S. and Van Reenen, J. (1998). Technology and changes in skill structure: Evidence from seven OECD countries. *Quarterly Journal of Economics*, 113(4):1215–1244.
- Malmendier, U. and Nagel, S. (2011). Depression babies: Do macroeconomic experiences affect risk taking? *Quarterly Journal of Economics*, 126(1):373–416.
- Manacorda, M. and Petrongolo, B. (1999). Skill mismatch and unemployment in OECD countries. *Economica*, 66(262):181–207.
- McConnell, M. M. and Perez-Quiros, G. (2000). Output fluctuations in the United States: What has changed since the early 1980’s? *American Economic Review*, 90(5):1464–1476.
- Mehra, R. and Prescott, E. C. (1985). The equity premium: A puzzle. *Journal of Monetary Economics*, 15(2):145–161.
- Melino, A. and Yang, A. (2003). State-dependent preferences can explain the equity premium puzzle. *Review of Economic Dynamics*, 6(4):806–830.
- Merz, M. (1995). Search in the labor market and the real business cycle. *Journal of Monetary Economics*, 36(2):269–300.
- Mincer, J. (1991). Education and unemployment. *NBER Working Paper*, 3838.
- Mishkin, F. S. (2017). Rethinking monetary policy after the crisis. *Journal of International Money and Finance*, 73(B):252–274.
- Miyata, S. (2002). Household’s risk attitudes in indonesian villages. *Applied Economics*, 35(5):573–583.
- Mortensen, D. and Pissarides, C. (1994). Job creation and job destruction in the theory of unemployment. *Review of Economic Studies*, 61(3):397–415.
- Mukoyama, T. and Şahin, A. (2006). Costs of business cycles for unskilled workers. *Journal of Monetary Economics*, 53(8):2179–2193.
- Mulligan, C. (2004). What do aggregate consumption euler equations say about the capital-income tax burden? *American Economic Review*, 94(2):166–170.
- Murphy, K. M. and Topel, R. H. (1987). The evolution of unemployment in the United States: 1968–1985. *NBER Macroeconomics Annual*, 2:11–68.

- Nickell, S. and Bell, B. (1996). Changes in the distribution of wages and unemployment in OECD countries. *American Economic Review*, 86(2):302–308.
- Nijman, T. and Verbeek, M. (1992). Nonresponse in panel data: The impact on estimates of a life cycle consumption function. *Journal of Applied Econometrics*, 7(3):243–257.
- Page, L., Savage, D. A., and Torgler, B. (2014). Variation in risk seeking behaviour following large losses: A natural experiment. *European Economic Review*, 71:121–131.
- Pålsson, A.-M. (1996). Does the degree of relative risk aversion vary with household characteristics? *Journal of Economic Psychology*, 17(6):771–787.
- Petrosky-Nadeau, N. and Wasmer, E. (2013). The cyclical volatility of labor markets under frictional financial markets. *American Economic Journal: Macroeconomics*, 5(1):193–221.
- Pissarides, C. (2009). The unemployment volatility puzzle: Is wage stickiness the answer? *Econometrica*, 77(5):1339–1369.
- Preuschoff, K., Bossaerts, P., and Quartz, S. R. (2006). Neural differentiation of expected reward and risk in human subcortical structures. *Neuron*, 51(3):381–390.
- Ravn, M. O. and Mazzenga, E. (2004). International business cycles: the quantitative role of transportation costs. *Journal of International Money and Finance*, 23(4):645–671.
- Rosenberg, J. V. and Engle, R. F. (2002). Empirical pricing kernels. *Journal of Financial Economics*, 64(3):341–372.
- Rudebusch, G. D. and Swanson, E. T. (2012). The bond premium in a DSGE model with long-run real and nominal risks. *American Economic Journal: Macroeconomics*, 4(1):105–143.
- Schmitt-Grohé, S. and Uribe, M. (2004). Solving dynamic general equilibrium models using a second-order approximation to the policy function. *Journal of Economic Dynamics and Control*, 28:755–775.
- Shimer, R. (2005). The cyclical behavior of equilibrium unemployment and vacancies. *American Economic Review*, 95(1):25–49.

- Simmons, A., Matthews, S. C., Stein, M. B., and Paulus, M. P. (2004). Anticipation of emotionally aversive visual stimuli activates right insula. *Neuroreport*, 15(14):2261–2265.
- Simmons, A., Strigo, I., Matthews, S. C., Paulus, M. P., and Stein, M. B. (2006). Anticipation of aversive visual stimuli is associated with increased insula activation in anxiety-prone subjects. *Biological Psychiatry*, 60(4):402–409.
- Stock, J. H. and Watson, M. W. (2002). Has the business cycle changed and why? *NBER Macroeconomics Annual*, 17:159–218.
- Stockman, A. C. and Tesar, L. L. (1995). Tastes and technology in a two-country model of the business cycle: Explaining international comovements. *The American Economic Review*, 85(1):168–185.
- Swanson, E. T., Anderson, G., and Levin, A. (2005). Higher-order perturbation solutions to dynamic, discrete-time rational expectations models.
- Szrek, H., Chao, L.-W., Ramlagan, S., and Peltzer, K. (2012). Predicting (un)healthy behavior: A comparison of risk-taking propensity measures. *Judgment and Decision Making*, 7(6):716–727.
- Tallarini, T. D. (2000). Risk-sensitive real business cycles. *Journal of Monetary Economics*, 45(3):507–532.
- Tanaka, T., Camerer, C. F., and Nguyen, Q. (2010). Risk and time preferences: Linking experimental and household survey data from Vietnam. *American Economic Review*, 100(1):557–571.
- Thoenissen, C. (2011). Exchange rate dynamics, asset market structure and the role of the trade elasticity. *Macroeconomic Dynamics*, 15(1):119–143.
- Topel, R. (1993). What have we learned from empirical studies of unemployment and turnover? *American Economic Review*, 83(2):110–115.
- van der Velden, R. and Bijlsma, I. (2016). College wage premiums and skills: A cross-country analysis. *Oxford Review of Economic Policy*, 32(4):497–513.
- Van Praag, C. M. and Cramer, J. S. (2001). The roots of entrepreneurship and labour demand: Individual and low risk aversion. *Economica*, 68:45–62.
- Vissing-Jorgensen, A. (2002). Limited asset market participation and the elasticity of intertemporal substitution. *Journal of Political Economy*, 110(4):825–853.

- Voors, M. J., Nillesen, E. E., Verwimp, P., Bulte, E. H., Lensink, R., and Van Soest, D. P. (2012). Violent conflict and behavior: A field experiment in Burundi. *American Economic Review*, 102(2):941–964.
- Ware, J., Kosinski, M., and Keller, S. (1995). *SF-12: How to score the SF-12 physical and mental health summary scales*. The Health Institute, New England Medical Center, Boston, MA.
- Weil, P. (1989). The equity premium puzzle and the risk-free rate puzzle. *Journal of Monetary Economics*, 24(3):401–421.
- Weil, P. (1990). Nonexpected utility in macroeconomics. *Quarterly Journal of Economics*, 105(1):29–42.
- Willinger, M., Bchir, M. A., and Heitz, C. (2013). Risk and time preferences under the threat of background risk: A case-study of lahars risk in Central Java. *Unpublished manuscript*.
- Wooldridge, J. M. (2002). *Econometric Analysis of Cross Section and Panel Data*. MIT Press, Cambridge, Massachusetts.